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Customer Service Experience of AI-Based Organisational Frontlines

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Abstract

Technological change, particularly the introduction of artificial intelligence (AI), is challenging traditional structures of organisational frontlines, especially in the service sector. Customers are increasingly interacting with machines that, although not human, display intelligence and other human-like behaviours. Hence, understanding how customers experience the service when interacting with these intuitive AI-based organisational frontlines is important for organisations.

Drawing on social exchange, use and gratification, and anthropomorphism theories, this research adopted a qualitative interpretivist approach to examine the role of intelligent virtual assistants as frontline employees. More specifically, the research examined their potential contribution to enhancing service encounters, while preserving the social and emotional aspects of interacting with human employees. To this end, 31 semi-structured interviews were conducted with users of Siri, Alexa, and Google Assistant around the world. To enhance data credibility, Leximancer was also used to examine 12,941 comments drawn from 81 YouTube videos whose content mentioned these intelligent assistants.

The research findings illustrate that when customers engage with intelligent assistants, anthropomorphic features, like voice recognition and mannerism, affect the type of gratifications (e.g., utilitarian, hedonic, and social) that users experience. Findings also suggest gratifications experienced diverge from previous research. This research also identifies that AI evokes a strong sense of social presence which gives customers the illusion of interacting with a human rather than a machine. In turn, this influences the formation and development of relationships between customers and AI-based frontline employees leading to enhanced customer engagement and building rewarding customer experiences.

This research contributes to current knowledge on organisational frontline studies by expanding use and gratification, social exchange, and anthropomorphism theories as well as the human-to-machine relationship literature. Nevertheless, AI and intelligent assistants are developing so rapidly that this may affect the results of this research by already ameliorating the customer experience of the offered service through the application of more advanced intelligent assistants.

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List of Abbreviations

OF: Organisational Frontline

FLEs: Frontline Employees

AI: Artificial Intelligence

M2M: Machine to Machine

ARA: Activity Resource Actor

Chapter 1 Introduction

1.1 Introduction

Customers are at the cutting edge of technology within most contemporary business contexts. Technology surrounds us and is already affecting everything from simple and mundane tasks to more complex operations, including the substitution of humans for machines. In the business world, AI-empowered technologies (e.g., robots, chatbots, and virtual assistants) that learn and adapt (i.e., intuitive AI) are revolutionising the nature of organisational frontlines, (understanding organisational frontlines as the study of interactions and interfaces at the contact points between an organisation and its customer) in terms of customer interactions and interfaces (Marinova, de Ruyter, Huang, Meuter, & Challagalla, 2017). Marinova et al. (2017) in their conceptual research, propose applying smart technologies to empower human frontline employees in relation to customer interactions. Extant research has focused on organisational frontlines (OF) in human-to-human contexts and concentrated on employees and the organisational context they work in (De Keyser, Köcher, Alkire, Verbeeck, & Kandampully, 2019; Huang & Rust, 2018; Karlsson & Skalen, 2015; Schneider & Bowen, 2019; Van Doorn et al., 2017). However, emerging technologies and particularly artificial intelligence (AI), are changing the organisational context to be more digital and virtual in nature. OF has been transformed in relation to interactions and interfaces because of the increasing acceptance of AI-empowered technologies in today's business world (Marinova et al., 2017). AI progression, and its integration within the service delivery process by organisations, demonstrates its potential as a component of OF (Gursoy, Chi, Lu, & Nunkoo, 2019). Potentially customers interact with technology through intelligent interfaces in service encounters. For instance, advanced voice-based capabilities make customers able to interact with complicated systems in natural, nuanced conversations. There is now widespread access to AI-empowered technologies through mobile phones, laptops, smartwatches, TV, etc.

There may co-exist supportive and preventive factors which influence AI-empowered technology acceptance behaviours of customers (Gursoy et al., 2019) to engage with them in service encounters and during service experiences. AI-resulted features (e.g., voice recognition and natural language processing) make human-to-machine interactions similar to human-to-human interactions. This similarity can add positive human attributes to machines as FLEs (e.g., voice recognition and natural language processing), however machines do not encompass human defects of character (e.g., fatigue, short-tempered, mood, etc.). Thus, machines can operate accurately and deliver predictable services and solutions in service encounters (Wirtz et al., 2018). AI-resulted features also enhance perceived gratifications by users (Cheng & Jiang, 2020b). Previous research investigated gratification and its effects on audience engagement with media and content to address their psychological and social needs (Gan & Wang, 2015; Mouakket, 2019; Zong, Yang, & Bao, 2019); and mainly focused on gratifications as antecedents of engagement. Also, AI-empowered technologies were studied as a medium of communication between two or more humans (Mouakket, 2019; Xu, Ryan, Prybutok, & Wen, 2012). However, now humans communicate with intelligent assistants not thinking of them as merely a medium of communication between humans, but as actors in their own right.

Such developments in AI also bring issues of uncertainty and trustworthiness insofar as individuals may not only be uncomfortable communicating with machines but also with their service capabilities. Ambiguities surrounding the algorithmic procedure of AI functionality create perceptions of privacy risk and uncertainty which affect trust and engagement with OF negatively. Research suggests that many customers do not trust the output of AI-empowered technologies (Davenport, 2019). In one instance of where human FLEs are superior to machine FLEs is in building and developing relationships, especially emotional relationships with customers in service encounters. Human FLEs can build emotional attachment with customers through socially interacting with customers and forming affective commitment towards the organisation. The current literature in business marketing does not acknowledge the affective commitment in human-machine relationships. Moreover, human FLEs have continuous contact with customers, co-create value (e.g., utilitarian, hedonic, and social) with them and support the value creating activities of customers (Karlsson & Skalen, 2015). Within high-touch, low-tech encounters (i.e., low level automation and where there is a high level of personal interaction) humans are crucial in communicating and creating satisfying social relations (De Keyser et al., 2019; Giebelhausen, Robinson, Sirianni, & Brady, 2014). However, increasingly humans are being substituted with AI-based machines, which are intellectually and behaviourally similar to humans.

This then guides us to the main research question and subsequent subordinate questions of this research:

RQ: How do intuitive AI-based organisational frontlines affect the customer service experience?

To address this key research question, it also requires the investigation of three other subordinate questions:

RQ1 How do intuitive AI-based organisational frontlines affect customer engagement in service encounters?

RQ2 How do intuitive AI-based organisational frontlines affect perceived gratification by customers in service encounters?

RQ3 How do intuitive AI-based organisational frontlines affect human-machine relationships in service encounters?

To address these questions, this research draws on social exchange theory, anthropomorphism theory, and use and gratification theory. As AI becomes part of every organisation's strategy to attain a competitive advantage, understanding customers-AI-based machine relationships becomes crucial. By answering the stated research questions, this research contributes to the literature on relationship marketing, anthropomorphism, and use and gratification theory.

1.2 Overview of Methodology

Adopting an interpretive paradigm, this research took a multimethod qualitative approach to answer the research questions. This comprised of using interview and secondary documents. Data was collected using 31 semi-structured interviews (the first participant was interviewed two times), and comments on 81 YouTube videos about Siri, Alexa, and Google Assistant posted between 2013 to 2020. The interviews were conducted with users of Siri, Alexa, and Google Assistant across the world. In collecting the secondary data, 12,941 separate comments were drawn from 81 YouTube videos about intelligent assistants (Siri, Alexa, Google Assistant) to triangulate interview data. Two types of coding were applied to classify data. First, the fully transcribed interview data was coded by the researcher intuitively with the help of theory and data management software NVivo. Second, secondary data was coded by applying computer-based coding (i.e., computer creates codes by algorithms) through Leximancer. The findings were then compared, categorised, and the results written up. Validity was ensured in all stages of data collection, data analysis, and reporting the results. This research initially undertook the inductive approach. Then while the research progressed, it moved towards the abductive approach to analyse the research data through systematic combining as Dubois and Gadde (2002) described.

1.3 Research Context

Recent technological advances feature a fusion of technologies which are developing exponentially. This fusion can be described better by AI. The term AI was first used in 1950 by Turing who used it to describe knowledge and engineering related to the building of intelligent machines (Jeste et al., 2020). The Turing test, also known as the "imitation game", is one of the philosophical foundations of AI (Proudfoot, 2013). It argues that a machine's intelligence is assessed "in its ability to produce a plausible conversation indistinguishable from that of a human" (Natale & Ballatore, 2020, p. 8). There have been many debates regarding the Turing test among scholars (Epstein, Roberts, & Beber, 2009) and the ability of machines such as Eliza to pass the test (Weizenbaum, 1966). Generally, the Turing test looks at how humans assess the proficiency of AI by understanding if the message is produced by a machine or human. From a social science perspective, it is not about the intelligence of machines (i.e., it is not about whether machines have truly achieved general intelligence), but rather it is about human's perception of what machines are capable of doing. This is especially in the era of virtual assistants (e.g., Amazon Alexa and Apple Siri) or chatbots (e.g., Replika (virtual AI friend on the App Store) that provide companionship), and how they can talk with humans as an autonomous agent (as if they are human). It is increasingly about how humans accept machines' behaviour and perceive them as intelligent. Correspondingly, Benlian, Klumpe, and Hinz (2020, p. 1016), in studying information and communication technologies, identified that "technology characteristics refers to individuals' perceptions or assessment of attributes or features of a particular information and communication technologies rather than what the information and communication technologies are objectively composed of, as it is primarily individuals' perceptions of technology features." Consistent with their conceptualisation, when referring to AI and its resulting anthropomorphic features, this research refers to human's perceptions and assessments of these features. In addition, Salles, Evers, and Farisco (2020, p. 88) and Nadji-Tehrani and Eslami (2020, p. 5257) refer to this new generation of AI as "brain-inspired AI" that evoke human anthropomorphised AI functionalities and innovations.

Anthropomorphism is described as the attribution of human characteristics (e.g., humanlike feelings, mental states, and behavioural features) to nonhuman entities (Epley, Waytz, & Cacioppo, 2007; Salles et al., 2020). Salles et al. (2020, p. 89) studied anthropomorphism in AI and illustrated that "anthropomorphism does not describe existing physical features or behaviours but rather represents a particular human-like interpretation of existing physical features and behaviours that goes beyond what is directly observable."

Epley et al. (2007) presented a psychological theory of anthropomorphism and introduced two motivational factors as main drivers of anthropomorphising non-human entities. First, humans need to experience competence which is about understanding (e.g., uncertainty), predicting, and controlling the surrounding world. Second, humans need and want to build social connections with other humans, and that in the absence of humans they try to form a humanlike connection with non-human entities (Epley et al., 2007).

1.4 The Scope of The Research

Different disciplines and literature define intelligence differently (Sternberg, 2005). Nonetheless, the principle of general intelligence has been defined as "general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly, and learn from experience" (Jeste et al., 2020, p. 994). It is generally about gaining and applying knowledge and skills. There are diverse theories of intelligence (e.g., Cattell's Gf-Gc theory and Cattell–Horn–Carroll's theory of cognitive abilities) that even though to some extent they are different, mostly agree on intelligence as a "a multifactorial construct comprised of several components, and integrates a number of cognitive domains and abilities, particularly sensory processing (including attention and working memory), language, acquired knowledge, memory consolidation and retrieval, processing and psychomotor speed, and reasoning" (Jeste et al., 2020, p. 995).

Artificial intelligence (AI) is the knowledge and engineering of constructing intelligent machines such as robotics, natural language processing, machine learning etc. (Ostrom, Fotheringham, & Bitner, 2019). AI systems encompass human intelligence components that include "reasoning, problem-solving, planning, learning, acting, reacting, and understanding and generating language" (Jeste et al., 2020, p. 996). Advanced AI is identified as artificial general intelligence (AGI) that accomplishes all of the abilities of human cognition (Jeste et al., 2020). Arguably, the aim of technological development is to imitate humans as closely as possible whilst serving them. However, reaching this point needs further development of the basic elements of general intelligence. Whilst AI is better than humans in some respects (e.g., pattern recognition and speed of processing), it still falls behind humans regarding reasoning and creativity (Jeste et al., 2020).

Computer science research classifies AI into three levels: artificial narrow intelligence, artificial general intelligence, and artificial super intelligence. Artificial narrow intelligence refers to the level of AI which is equal or superior to human intelligence at solving narrow problems, while artificial general intelligence is equal to human-level intelligence at solving any kind of problem. Artificial super intelligence is described as the level of AI which is more advanced than humans in every field (Ammanath, 2016). However, computer scientists have different opinions about moving from the artificial narrow intelligence level to the artificial general intelligence level at the current time (Epstein et al., 2009). In marketing science, Huang and Rust (2018) studied artificial intelligence in services, and categorise artificial intelligence into four groups (i.e., Mechanical, Analytical, Intuitive, and Empathetic) based on human intelligence. They discuss different AI's applications in service, drawing on Sternberg (2005) research on theory of intelligence and Goleman (1996) research on emotional intelligence. This research selects intuitive AI from Huang and Rust's (2018) AI classification, because based on their criteria, this level of AI applies deep learning (i.e., a progressive computing system) that can teach itself to discover and classify patterns or anomalies to predict future actions and make recommendations (Tibbetts, 2018). These result in humanlike interactions with customers in service encounters (e.g., reciprocal voice-based interactions). Also, " Intuitive intelligence is of great value for the task of relationship-based personalisation (Huang & Rust, 2018, p. 164)" which plays a significant role in building the customer service experience. Consequently, it could help to address needs for further research on frontlines in integration with emerging technologies (e.g., AI) (Rafaeli et al., 2017). Rafaeli et al. (2017, p. 97) call for research about "psychological mechanisms that contribute to the transfer of technological functionalities to customers' value experience" and "examining how trade-offs between (information) control, privacy concerns, and empowerment are made in frontline service encounters and redefine the roles of both employees and customers."

Intuitive AI in this research refers to the level of artificial intelligence with the ability of creative thinking that can adapt efficiently to new situations. Intuitive AI is designed to adopt a significant part of human cognition and learn the same as a human (Huang & Rust, 2018; Wirtz et al., 2018). It gives the illusion of interacting with a human to users which results in users attributing human characteristics (i.e., anthropomorphism) to the AI-based agents (Salles et al., 2020). This research therefore studies how intuitive AI and its resulting anthropomorphic features effect the human-to-machine interactions and the experience of customers during these interactions in service encounters.

The aim of this research was the study of customer experiences of intuitive AI-based organisational frontlines. For the purpose of this research, the organisational frontline refers to the study of the organisation's contact points with its customers that include frontline employee, frontline technology, frontline interaction, and frontline interface (Singh, Brady, Arnold, & Brown, 2017). This research studied intelligent conversational assistants (i.e., Siri, Alexa, Google Assistants) as an intuitive AI-based organisational frontline because these intelligent assistants benefit from this level of AI based on the Huang and Rust (2018) classification and they can take the role of frontline employee (e.g., when human ask for information or service), frontline technology, frontline interface that frontline interactions happen on them. In this research context, the human intelligent agent interaction points to "the intersection of artificial intelligence, social science, and human-computer interaction (HCI)" (Miller, 2019, p. 5). See Figure 1.1

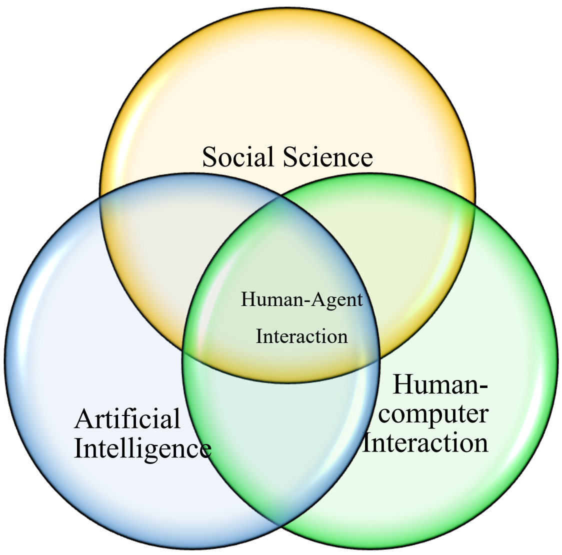

Figure 1-1: Scope of Intelligent Assistant (Miller, 2019, p. 5)

1.5 The Structure of The Thesis

This thesis consists of six chapters. Chapter 1 introduces the organisational frontline, the ubiquity of AI technology and its integration within service contexts demonstrating the necessity of understanding customer behaviour in the AI-based service encounters. In doing so it highlights the importance of social and emotional relationships in AI-based service encounters and the lack of research in this area. Next, the research questions are proposed, the methodology is outlined, and the research scope is established.

Chapter 2 reviews related literature on the research topic. It starts with an introduction of the organisational frontline, its components (i.e., interaction and interfaces) and the effects of technology, especially AI, on organisational frontlines. Subsequently, literature on AI is presented, introducing intuitive AI and its impacts on anthropomorphism and machine behaviour. This chapter moves on to introduce customer engagement and its dimensions. It then examines different gratifications that can be obtained through engaging and interacting with another party in the relationship. The next section in this chapter presents relational factors and the final part concludes with the customer experience. Chapter 2 also identifies the research gaps and the research questions that this research aims to answer in order to address these gaps.

Chapter 3 outlines the methodology of this research. It clarifies the philosophical approach guiding this research and illustrates how this is justified by the nature of the research questions, the methods of data collection and analysis. Following on, this chapter details the qualitative interpretivist approach taken by this study and provides more information about data collection and data analysis. Finally, this chapter addresses how validity, reliability and ethicality were ensured by focusing on the process of designing, collecting and analysing data.

Chapter 4 presents the findings of this research in two key parts. The first part presents the findings from interviews following the logic of the service experience; how customers engage with intelligent assistants for the first time and how they experience their service journey. The second part presents findings from the analyses of the secondary data based on themes identified by Leximancer software.

Chapter 5 discusses the research findings with respect to the research aims and the existing literature. It provides discussion around major themes derived from the research: customer service experience, anthropomorphism, engagement, gratifications, and relational factors. In addition, this chapter references relevant literature to explain identified patterns.

Chapter 6 summarises the research results, articulates the research contributions to the literature, and presents a number of practical implications that arise from the research findings. This chapter also highlights the limitations of this research and proposes directions for future research.

Analysing research data illustrates that anthropomorphic features resulting from intuitive AI embedded in current AI-empowered technologies (e.g., cognitive intelligence, reciprocal voice-based interactions, and mannerism) give the appearance of being more human-like. Therefore, this results in an increased sense of social presence, which fosters distinct gratifications and experiences for users of AI-empowered technologies that are significantly different from previous technologies. Consequently, anthropomorphic features and obtained gratifications from interacting with intuitive AI-empowered technologies affect the creation and development of human-intelligent machine relationships differently.

Chapter 2 Literature Review

2.1 Introduction

This research aims to explore the customer service experience of intuitive AI-based organisational frontlines. Organisational Frontlines are the study of interactions and interfaces between an organisation and its customers in their contact points. The nature of frontline interactions and interfaces have changed to be more virtual and intelligent by emerging technologies. AI is one emerging technology that potentially offers the opportunity at the organisational frontline to interact with customers in a human-like way. Moreover, artificial intelligence adds cognitive and behavioural characteristics to the intelligent interfaces (e.g., intelligent assistants) that make them even more humanlike. These human likenesses cause customers to attribute human features to machines and anthropomorphise them. Anthropomorphism may have implications for the acceptance of such organisational frontlines and the nature of customer engagement with them. Consequently, AI may change the service experience, the customer journey and the way customers engage with the frontline employees and the gratifications (e.g., utilitarian, hedonic, and social) they achieve from interacting with them. In turn, obtained gratifications may affect customers' motivation for subsequent engagements and the forming of a relationship with the organisation. To conclude, customers engagement and interaction with organisational frontlines form their experience of the shopping journey.

This chapter starts with the main construct of the research (section 2.2) - organisational frontlines. In doing so it aims to create a better understanding of the organisational frontline and to use this to inform the basis of the customer service experience. Because the customer service experience is investigated from the perspective of an ecosystem, the customer journey covers a range of dimensions that encompass customer engagement with frontline employees, receiving the service, customer perceptions about the service itself, service delivery, and forming relationships that lead to reengagement. To reflect this, the chapter is structured as follows.

Section 2.3 explains the theoretical background of the research. As intelligent assistants become more human-like (cognitively and behaviourally) due to applying intuitive AI, they are different from other available technologies. Hence, existing theoretical foundations and models (i.e., Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) models) may not be enough to explain a human’s behaviour towards the technology as they only investigate utilitarian benefits (e.g., ease of use and usefulness) of virtual conversational assistants (Fan, Liu, Wang, & Wang, 2017; Ramirez-Correa, Grandon, Ramirez-Santana, & Belmar Ordenes, 2019). However, intuitive AI and its resulting anthropomorphic features have transformed the way humans perceive and interact with intelligent assistants, to the extent that users form a deeper connection with machines (Pitardi & Marriott, 2021). Therefore, this study draws on social exchange theory to examine the probability of human-machine relationships because customers frequently develop relationships with human frontline employees. This research also applies use and gratification theory to understand the drivers that humans have to engage with the intelligent assistants to address what they want. Finally, due to the anthropomorphic features of intelligent assistants, this research applies anthropomorphic theory to explain why users attribute human features to machines. Next, it moves to section 2.4 (AI) which is the main reason of anthropomorphising machines.

Section 2.5 examines customer engagement and explains the antecedents of customer engagement. Subsequently, it moves to section 2.6 to explain the next stage of the customer service experience (i.e., gratification). When customers engage with intelligent assistants to receive a service, they may be uniquely gratified by this service and consequently their intention to reengage, and this leads us to section 2.7. Users who feel gratified build different forms of relationships with intelligent assistants that affect their intention to reengage with them. Finally, section 2.8 concludes all previous parts of the customer service experience.

2.2 Organisational Frontlines

The word "frontline" originates from its application in the military around the middle ages. Later, it entered the management field and has expanded through time. The first introduction of “frontline” to the service field was to identify employees at a point of customer contact and service (Singh et al., 2017). The study of organisational frontlines comprises a range of interdisciplinary subjects that connects computer science, information systems, management, marketing and services to the extent that they investigate the contact points of customers with organisations reflective of their own individual disciplines (Singh et al., 2017).

The organisational frontline comprises all of the contact points between an organisation and its customers and includes: Frontline Employees (FLEs), Frontline Service Technology (FST), Frontline Interactions and Frontline Interfaces. In other words, Organisational Frontline (OF) is "the study of interactions and interfaces at the point of contact between an organisation and its customers that promote, facilitate, or enable value creation and exchange" (Singh et al., 2017, p. 4). These interactions and/or interfaces can include people, technology, AI or even a combination of these. Customers, suppliers, and employees are the main stakeholders in the organisational frontline (Ma & Dube, 2011). From a technological perspective, it can be defined as each compound of software, hardware, information and/or networks which backup value co-creation between customer and provider in the organisational frontline. The organisational frontline is also illustrated as distinct interactions or touch points between customer and service provider (De Keyser et al., 2019; Huang & Rust, 2018).

The research domain of the organisational frontline is specified by its elements comprising interfaces and interactions. It consists of different kinds of interaction which are provided by selecting specific interfaces such as ATMs and service robots (Singh et al., 2017). Understanding frontline interactions without considering interfaces is impossible. Every combination of interaction-interface illustrates a unique composition (Giebelhausen et al., 2014). In the following sections the literature on organisational frontline components will be reviewed in more detail.

2.2.1 Frontline Employees (FLEs)

Frontline employees are employees that have continuous contact with customers, co-create value with them and support value creation of customers (Karlsson & Skalen, 2015). In "high-touch, low-tech" service encounters, frontline employees play an important role in driving successful service encounters by building positive social relationships (De Keyser et al., 2019; Giebelhausen et al., 2014). In addition, by combining knowledge and skills, frontline employees contribute to service innovation, since they can collect information from different sources such as customers and obtain knowledge about customer's requirements, expectations, and needs (Karlsson & Skalen, 2015). Consequently, frontline employees can meet the expectations of both customers and firms. Frontline employees are mostly put in a situation in which they must accomplish their job requirements and meet customer demands simultaneously. Moreover, practices and processes which are communicated by an organisation through frontline employees have an indirect effect on customer response behaviours (Jha, Balaji, Yavas, & Babakus, 2017).

Increasingly, frontline service technology is modifying and transforming interactions between customers and frontline employees (De Keyser et al., 2019; Giebelhausen et al., 2014; Marinova et al., 2017; Van Doorn et al., 2017). The rapid development of technology (e.g., artificial intelligence) is changing service characteristics particularly related to robotics in combination with big data, artificial intelligence, digital devices and cloud technology, sensors and etc. (Wirtz et al., 2018). Hence robots in association with artificial intelligence and machine learning have become attractive to business experts and service researchers within the context of frontlines (Marinova et al., 2017; Van Doorn et al., 2017; Wirtz et al., 2018).

2.2.2 Frontline Service Technology

Frontline service technology infusion connects service organisations to the customer's frontline experience via technological elements (Van Doorn et al., 2017). Frontline service technology is currently ubiquitous and boosts various service encounters such as technology-based human-to-human, human-to-technology and technology-to-technology service encounters (De Keyser et al., 2019).

Froehle and Roth (2004), regarding the importance of technology in face-to-face and face-to-screen encounters, present five conceptual service encounter archetypes: technology-free customer contact; technology-assisted customer contact (i.e. technology supports frontline employees); technology-facilitated customer contact (i.e. technology supports frontline employees and customer); technology-mediated customer contact (i.e. frontline employees and customers connect to each other by technology); and technology-generated customer contact (i.e. self-service technology) (De Keyser et al., 2019; Froehle & Roth, 2004; Glushko & Nomorosa, 2013).

The main application of frontline service technologies is as a facilitator of value creation between a customer and a provider in the exchange process. Technology can be complementing and augmenting human capabilities. Hence, collaborating human and technology can enhance humans ability (e.g., human thinking, analysis and behaviour) to interact with other humans. Nevertheless, in the value creation process, smart and connected technologies can act autonomously without any exterior intervention (De Keyser et al., 2019; Froehle & Roth, 2004; Glushko & Nomorosa, 2013).

The most important tasks of frontline service technologies are human augmentation (complements) or substitution. The human augmentation role of frontline service technologies consists of assisting and complementing human customers and/or frontline employees to fulfil their duties better and meet the goals in the service encounter (De Keyser et al., 2019; Marinova et al., 2017). It is often labelled as 'intelligence augmentation' due to supporting human thinking, analysis, and behaviour. Technology as augmentation can be applied alongside humans to provide a superior service encounter outcome (Larivière et al., 2017). Whereas, frontline service technology's substituting role is related to automating and replacing humans with the technology in the service encounter (De Keyser et al., 2019; Marinova et al., 2017). In other words, substituting a human agent by technology in the service encounter indicates that human duties are done by a technology-driven counterpart (De Keyser et al., 2019).

2.2.2.1 Human Augmentation Roles of Technology

A customer/technology-assisted FLE encounter (e.g., computer-assisted check-in) is where the frontline employee is complemented/augmented by technology to have faster, cheaper, personalised and positive interactions with customers through physical presence (De Keyser et al., 2019; Larivière et al., 2017).

In the technology-assisted customer/FLE encounter (e.g., price-comparison mobile applications) the customer is complemented/augmented by technology while FLEs have a physical presence in service encounters. This category of encounter has been significant as all customers are connected by their smart devices (e.g., mobile phone, smart watch) to real-time information resources (e.g., websites) as an alternative to frontline employees guiding service interactions (De Keyser et al., 2019).

A customer/FLE technology-facilitated encounter (e.g., self-check-in machines), include real-time encounters, in that customers and frontline employees can use the same augmenting technology while both customers and FLEs have a physical presence in service encounters. This type of service encounter facilitates value creation through improving the resource exchange process which leads to developing interaction capabilities and value co-creation for both parties (De Keyser et al., 2019).

A customer/FLE technology-mediated encounter (e.g., phone-assisted booking) includes encounters in that both frontline employees and customers are not physically co-located and instead use technology to interact with each other (De Keyser et al., 2019; Froehle & Roth, 2004). The most common examples of these encounters are phone, email, chat, instant messaging. The value of this type of service encounter lies in remote service delivery which leads to convenience and cost saving for both parties (De Keyser et al., 2019).

2.2.2.2 Human Substitution Roles of Technology

The technology-substituted customer/FLE encounter (e.g., remote monitoring and repair services) includes service encounters in which customers are replaced by technology. In this type of service encounter, decisions are taken autonomously for the customer or based on pre-determined customer preferences. For instance, Google Duplex can make calls for users to book appointments and reservations. In other words, a customer substituted with a technological counterpart in interaction with frontline employees (De Keyser et al., 2019).

The customer/technology-substituted FLE encounter (e,g., ATMs), entails encounters where frontline employees are being substituted by technology and customers interact with a technological interface without having direct interaction with human employees. This kind of encounter is the most common substitution archetype. The development of AI can increase the diversity of examples of this type of service encounter. These encounters bring cost-savings for the organisation, as well as convenience and satisfaction that results from participating actively for the customer (De Keyser et al., 2019).

The full technology encounters (e.g., Machine-to-Machine (M2M) automated utility billing) are where frontline employees and customers are substituted by technology with different autonomy levels. In such encounters, active engagement is no longer necessary between both parties for service to take place. In addition, development in the internet of things (IoT) field or M2M service interactions develop this service archetype (De Keyser et al., 2019; Van Doorn et al., 2017). As internet of things applications develop, these kind of encounters will become more widespread and significant. In that, without any cooperative act from operating frontline employees or customers, the service process operates autonomously. The value of technology replacement is in cost-savings for the provider and a more convenient and faster service for customers (De Keyser et al., 2019).

The infusion of technology into service processes and service encounters leads to changes about the various ways service delivery affects the customer experience. Service encounters have been transformed by technology due to substituting interpersonal interactions with information exchanges (Glushko & Nomorosa, 2013). Although these technological changes have transformed organisational frontlines, our understanding of the effects of these technologies on service encounters is limited (De Keyser et al., 2019).

2.2.3 Frontline Interactions

Today's modern communication arena represents infinite ways to interact and support customers by organisations (Temerak, Winklhofer, & Hibbert, 2018). Accordingly, in the competitive service environment, the way in which frontline employees interact with customers may be a competitive advantage resulting in profits for the service organisation (Yoo, 2017).

Interaction was originally considered as a mechanism to facilitate the exchange process. It includes costs and benefits for engaged actors in the interaction (Ford & Hakansson, 2013). Interactions comprise of the characteristics of actions, communications, and processes that happen during the contact of the customer with the organisation (Singh et al., 2017). Customers of service organisations often interact with frontline employees at first and sometimes only with them (Albrecht, Hattula, Bornemann, & Hoyer, 2016). In other words, the main focus of service lies in the way frontline employees interact with customers (Lee, 2017; Yoo, 2017) and transfer service quality (Jha et al., 2017). As a result, the better the frontline employee fulfil their responsibilities in service encounters, the higher the interaction quality and sales performance (Jha et al., 2017).

Interactions in the business landscape have diverse forms, such as human-to-human, human-to-machine, and machine-to-machine interactions. Human-to-machine interaction is the interaction between computerised systems, computer or smart devices and humans, where they apply their interaction methods (e.g. touchscreens, keyboards, voice input, etc.) (Martins, Santos, & Dias, 2019). Human-to-machine interaction is an interdisciplinary branch of knowledge that points to the connection of human and technology (Pomboza-Junez, Holgado-Terriza, & Medina-Medina, 2019). Online interactions, as a kind of human-to-machine interaction, empower organisations to interact with a large number of customers (Alnsour, 2018).

Machine-to-machine interactions include independent interactions of machine devices without human intervention to measure, process and do application activities (Amodu & Othman, 2018). A lack of human presence in machine-to-machine interactions distinguishes it from other kinds of interaction, and from this viewpoint investigating it and its impact on customer-frontline employee relationships could be rewarding. The most important usage of machine interactions is in various applications (Amodu & Othman, 2018), which are on inseparable part of our life today.

Growing relational interactions between customers and frontline employees have had a positive impact on the dimensions of the relationship quality such as trust, commitment, and satisfaction (Alnsour, 2018). Also, interpersonal interactions are the perfect kind of knowledge resource, as they help customers by giving them access to experience-based knowledge (Temerak et al., 2018). In face-to-face service encounters due to bilateral interactions, both customer and frontline employees influence each other's experience and activity. The quality of interpersonal interactions in a service encounter influences service outcomes (e.g., customer experience and perception) (Di Mascio, 2010; Ma & Dube, 2011).

Smart technologies are changing frontline interactions. When service coproduction is enhanced with applying smart technologies, customers and frontline employees can gain knowledge through interactions and improve their interactions in real time (Marinova et al., 2017). As mentioned in previous sections, these technologies may be used by either customer or frontline employees, or jointly by both. In addition, smart technologies in technology-mediated interactions increase the importance of frontline employee’s social interaction skills to make sure that interactions take place effectively over such interfaces (Singh et al., 2017). Customers place high importance on social interactions with frontline employees in service encounters to build an enjoyable interaction with a service provider (i.e., rapport) (Giebelhausen et al., 2014).

The Activity-Resource-Actor (ARA) model (Håkansson & Johanson, 1992) provides a conceptual interaction framework which illustrates the interaction’s outcome in three layers: activity links, resource ties and actor bonds. These layers are interconnected, influence and are influenced by each other. The activity layer is about activities that connect one actor to another (e.g., production, administration, delivery, and information handling). The resource layer is about shared resources by actors that tie them together. These resources can include physical facilities or even knowledge. This layer could be effective regarding innovation. The actor bond layer refers to the interpersonal and social links developed between parties through interaction. This layer is created according to both party's knowledge about each other, feelings of closeness, how they can trust and/or affect each other and become committed. It is therefore necessary to investigate trust and commitment in this layer when substituting one or both parties with machines in interactions (Ford & Hakansson, 2013; Lenney & Easton, 2009).

2.2.4 Frontline Interfaces

Interfaces act as a means of interaction between actors to transfer information or services (Deng, Wang, & Yu, 2016; Kirisci & Thoben, 2018). Specifically, interfaces are the required instrument to actualise the interaction, which is information processing between human and machine (Deng et al., 2016). Interfaces encompass the characteristics of modes, agents, artifacts, and servicescapes and serve as the mediator for the contact of the customer with the organisation (Singh et al., 2017).

Service organisations apply numerous interfaces to interact with their customers. However, sometimes they use these interfaces without having information about a customer's preferences for interacting specifically in multi-interface environments. Moreover, the diversity of interfaces helps customers to have the required resources for co-production activities (Temerak et al., 2018).

Customer interfaces are classified as face-to-face and face-to-screen (Scerri & Agarwal, 2018). The face-to-screen interface (i.e., user interface) is an online interface which is a platform for offering customers value propositions and resources (Li, Huang, Yeung, & Jian, 2018). Offline interfaces are considerably different from online interfaces and consequently affect customer experiences in different ways. For instance, in face-to-face interfaces, the customer-employee relationship's closeness positively influences customer behaviour on purchasing or recommending (Lee, 2017).

The service interface and service delivery method affect the customer experience. Personalised services that can be provided via an adaptive and interactive user interface impact customer experience more (Hussain et al., 2018; Temerak et al., 2018). In this regard, a measure for testing a customer's attention, time, ease, effectiveness, and satisfaction towards an interface is usability. Usability is explained by users attaining their aims in a given environment with effectiveness, efficiency, and satisfaction. The absence of usability creates dissatisfaction, frustration, etc., which leads to not using the interface (Nazrul Islam & Tétard, 2014).

From a different perspective, online interfaces as a part of service encounters determine the delivery time or waiting time (i.e., time spent in queue and production time) in exchange processes (Marino, Zotteri, & Montagna, 2018). This results in replacing human interactions with machines. It eradicates human errors and accelerates interaction between frontline employees and customers when time plays a significant role. Technology-based interfaces enhance customer experiences through improving customer convenience (i.e., minimising time and endeavour to gain a service) (Benoit, Klose, & Ettinger, 2017).

Research shows time-sensitive customers prefer to select service providers that are anticipated to offer services in a shorter time (Benoit et al., 2017; Marino et al., 2018). Even in off-line interfaces customers who experience time pressure believe that the lack of time to complete their shopping process leads to negative emotions such as feeling hurried or rushed (Benoit et al., 2017). Also, from an economic perspective, the time each customer spends shopping is considered as opportunity costs (Marino et al., 2018).

Utilising emerging technologies as an interface (e.g., AI, internet, mobile phone) to provide service through technology-based interactions between customers increases a customer's utilitarian (e.g., efficiency and convenience, having more control), hedonic (e.g., pleasure) and social benefits (e.g., increasing self-image) (Lee, 2017). Intelligent user interfaces (e.g., Siri and Alexa) are one type of these interfaces which are developed from the intersection of AI and human-computer interaction (Lester, 2001). These interfaces are the mediator of relational exchanges between customers and organisations, which result in online relationships between them. Online relational contexts are essentially different from offline relationships. Consequently, how online relationships form and develop in these new and distinct contexts is important (Steinhoff, Arli, Weaven, & Kozlenkova, 2019). Relationship marketing utilises different theories to study the exchange and development of the relationship between customers and organisations.

2.3 Theoretical Foundations

This study is anchored on the theories of social exchange, use and gratification, and anthropomorphism. As each of these views look at the various aspects of the human-machine relationship and deal with diverse angles in investigating the customer service experience, it is necessary to include them when studying the customer service experience of AI-based organisational frontlines.

2.3.1 Social Exchange Theory

Social exchange theory is a multi-disciplinary theory which is derived from psychology, economics, and sociology (Hsu, Yin, & Huang, 2017). It argues that an individual's behaviour depends on perceived benefits and costs (Hsu et al., 2017; Jin, Li, Zhong, & Zhai, 2015). The benefits include rewards (e.g., respect, and reputation) and highlight unspecified obligations that are intangible. Hence, social exchange tends to create "feelings of belonging, personal obligation, gratitude, trust, and loyalty" (Jin et al., 2015, p. 842).

Social exchange theory takes an open approach to the relationship. It has been used by scholars to illustrate the antecedents and dynamics of relationship success for buyers and suppliers (Ambrose, Marshall, & Lynch, 2010). At any point in time, individuals decide to enter an exchange due to the exchange history as well as the benefits they expect from the exchange (Hsu et al., 2017).

Social exchange theory is a broad theory that provides an interpretive description for different outcomes that can be created from an individual's or organisation's interactions. One of these outcomes is trust in interpersonal or inter-organisational exchanges. That is explained based on the key theme of reciprocity, which explains an action or behaviour of one party in the interaction will lead to reciprocal action or behaviour by the other party. In other words, each party is obligated to return any advantages received (Ambrose et al., 2010; Hsu et al., 2017; Lioukas & Reuer, 2015).

The bilateral reciprocation of beneficial action over time via multiple interactions lead to building trust. Consequently, the process of building trust creates obligations amongst exchange partners (Lambe, Wittmann, & Spekman, 2001). According to social exchange theory, the principle of generalised reciprocity is the main reason for the causal relationship between trust and commitment, which suggests “mistrust breeds mistrust and as such would also serve to decrease commitment in the relationship and shift the transaction to one of more direct short-term exchanges” (Lambe et al., 2001, p. 11). Mutual commitment plays a significant role in functional social exchange as it ensures that relationship parties will put in effort and essential investments to create mutually favourable outcomes. (Lambe et al., 2001). Accordingly, an underlying premise and main context of social exchange theory is the significance of trust and commitment to ensuring relationship success (Ambrose et al., 2010; Hsu et al., 2017; Morgan & Hunt, 1994).

Online interactions lack face-to-face interactions and require trust between parties. As trust is created and built between exchangers, online transaction uncertainty and risk are decreased and an affirmative intention towards transaction behaviour is built (Hsu et al., 2017). Plus, trust is considered as a consequence of diverse exchange relationships (Lambe et al., 2001; Lioukas & Reuer, 2015).

Through time, social outcomes and positive economic circumstances lead to increasing the partners' commitment and trust towards each other and preserving the exchange relationship. Moreover, positive exchange interactions over time create relational exchange norms that govern the interactions of exchange partners (Lambe et al., 2001).

From the social exchange theory viewpoint, exchange interactions involve economic and/or social outcomes. Across time, in the exchange relationship, each party compares the social and economic outcomes of exchange interactions with outcomes from alternative exchange interactions. The result of this comparison reveals each party’s dependence on the exchange relationship (Lambe et al., 2001). Social exchange theory demonstrates that individuals or groups interact together based on the reward expectation or punishment avoidance (Ambrose et al., 2010). In addition, the relational interdependence or relational contract is the core explanatory mechanism of social exchange theory that expands through the interactions of the exchange partners with time (Lambe et al., 2001).

Since social exchange theory sheds light on the relationship between the exchange parties as the governance mechanism of exchange, it is especially beneficial for explaining customer-organisational frontline relational exchange (Lambe et al., 2001).

2.3.2 Use and Gratification Theory

Use and gratification theory is rooted in psychological and social needs (Lien & Cao, 2014) which is increasingly relevant to the mass communication paradigm (Cheng & Jiang, 2020a). This theory demonstrates why and how individuals use special media to meet special needs. Use and gratification theory explains that the special use of a media is based on the expected and experienced gratifications of that media (Brandtzaeg & Følstad, 2017; Cheng & Jiang, 2020a; Mouakket, 2019). Moreover, this theoretical approach is applied to identify the psychological needs and gratifications of adopting a particular media (Mouakket, 2019). However, some scholars criticise use and gratification theory since it only lists the reasons why users apply specific media (Chavez, Ruiz, Curras, & Hernandez, 2020).

Use and gratification theory builds upon principles that users play an active role (i.e., users are goal-oriented) in choosing and using a specific media according to social and psychological needs or gratifications (Abrantes, Seabra, Lages, & Jayawardhena, 2013; Brandtzaeg & Følstad, 2017; Chavez et al., 2020). This theory assumes that users have an active part in selecting the best media when they have alternatives to reach their goals by different media (e.g., webpage, apps, etc.) (Chavez et al., 2020). In addition, use and gratification theory proposes that gratifications impact a user’s attitudes, and these attitudes direct a user's usage and engagement. (Chavez et al., 2020).

The use and gratification approach has been discussed as a suitable approach to comprehend a user’s motivations regarding the use of traditional and online media (Mouakket, 2019). Use and gratification approach has been studied recently in computer-mediated communication technologies like chatbot (Cheng & Jiang, 2020a), social media (Gan & Wang, 2015), online gaming (Li, Liu, Xu, Heikkila, & van der Heijden, 2015), internet (Abrantes et al., 2013), augmented reality (Jang & Liu, 2019), mobile instant messaging applications (Mouakket, 2019), to understand the motivation of using these technologies. However, new smart technologies due to AI can include cognitive aspects which make machines appear more humanlike when communicating directly with humans and not as a mediator. How these human similarities (i.e., anthropomorphism) can affect perceived gratifications and in turn motivations to use AI-based technologies requires investigation.

2.3.3 Anthropomorphism Theory

The theory of anthropomorphism describes when people are likely to anthropomorphise by concentrating on three psychological factors: "the accessibility and applicability of anthropocentric knowledge (elicited agent knowledge), the motivation to explain and understand the behaviour of other agents (effectance motivation), and the desire for social contact and affiliation (sociality motivation)" (Epley et al., 2007, p. 864).

Anthropomorphism is determined by both cognitive and motivational determinants. The first determinant of anthropomorphism is the elicitation of agent knowledge itself (i.e., cognitive determinant). Having knowledge about humans builds the basis for induction as this knowledge is acquired earlier and is more comprehensive than knowledge about non-human agents. In addition, anthropomorphism is evoked through two motivational factors (Epley et al., 2007). The first is the necessity of effectance. Humans try to create a sense of mastery and control through delineating the familiar concept of humans onto incomprehensible entities (Salles et al., 2020). As humans need to experience competence to understand, predict, and control uncertainty and make sense of that for interacting with the surrounding environment (Salles et al., 2020). The second is the necessity of social connection. Humans who need connection (e.g., lonely people) by anthropomorphising non-human entities build these relationship partners to get pleasure from the sense of relatedness (Epley et al., 2007; Tam, 2015). In the absence of humans those who interact to build social bonds can still develop human-like connections with non-human entities (Salles et al., 2020). AI, as a revolution in a technological world, enhances social networking between humans and machines and increases machines' social attributes (e.g., social presence and social cognition) (Pitardi & Marriott, 2021), facilitating social interactions and connections.

2.4 Artificial Intelligence

Contemporary digital services become more reliant on intelligent and interconnected devices. Intelligent machines have reached capabilities that go beyond a human level (Huang & Rust, 2018). In human intelligence literature, "intelligence" is explained as the ability to learn from experiences over time and to be compatible with the environment (Sternberg, 1999). From the bio-psychological viewpoint, intelligence is the capability of processing information and conditions to address problems (Huang & Rust, 2018). Parallel with that, "Artificial Intelligence (AI)" is the knowledge and engineering of constructing intelligent machines such as robotics, natural language processing, machine learning etc. (Ostrom et al., 2019). AI has become prevalent in today's society as it integrates both physical and cognitive domains. Cognitive capabilities provide the ability to machines to understand and analyse their environment, reason, make decisions, and perform actions (Naqvi, 2017). Moreover, AI elaborates human aspects in machines. Its use increasingly grows in the service industry and it becomes a source of innovation (Huang & Rust, 2018).

Services can be provided by human and/or machines. According to the service type, different intelligence is required from human intelligence to artificial intelligence. Four kinds of AI (i.e., mechanical, analytical, intuitive, and empathetic) are introduced in the literature (Huang & Rust, 2018).

Mechanical intelligence

Mechanical intelligence relates to the ability to do routine and repetitive tasks automatically. This kind of intelligence is not very smart and creative (Huang & Rust, 2018; Lu, Li, Chen, Kim, & Serikawa, 2018; Ostrom et al., 2019; Wirtz et al., 2018).

Analytical intelligence

Analytical intelligence refers to the ability of information processing, reasoning, and mathematical skills for problem solving and rule-based learning. Analytical skills are achieved through training, experience, and specialisation in cognitive thinking (Huang & Rust, 2018; H. M. Lu et al., 2018; Ostrom et al., 2019; Wirtz et al., 2018).

Intuitive intelligence

Intuitive intelligence is the ability of creative thinking and adapting efficiently to new situations. This level of intelligence is based on wisdom in a holistic way and relying on experience (Huang & Rust, 2018; Ostrom et al., 2019). Intuitive intelligence composes professional skills of high level thinking which needs intuition and creative problem-solving (Huang & Rust, 2018).

Intuitive Intelligence lies beyond the boundaries of science and analytics. It bridges the realms of reality and imagination, reason and instinct, material and spiritual dimensions of human existence (Bolton et al., 2018). What distinguishes intuitive AI from other kinds of AI is understanding. Intuitive AI which is labelled as “strong AI” in AI literature (Huang & Rust, 2018), works in a more dynamic way and more like a human. Furthermore, intuitive AI is constructed to operate a significant part of human cognition and to learn the same as a human child but in a rapid way because of its technological prominent features (Huang & Rust, 2018; Wirtz et al., 2018). It is claimed by Huang and Rust (2018) that intuitive AI has all the features of human intelligence, and because of its learning power from experience, it seldom makes the same mistake twice. Intuitive intelligence is necessary to perform complicated, creative, experiential, disordered, holistic, and context-based tasks (Huang & Rust, 2018; Wirtz et al., 2018).

Empathetic Intelligence

Empathetic intelligence refers to the ability to identify and understand the emotions of others and respond to them at an emotional level. It contains social and interpersonal skills that encompass the need to be sensitive about the feelings of others. Empathetic AI equips machines with the power of sensing other's feelings or behaving in a way that demonstrates feelings. Its unique difference is the ability to experience things. Empathetic AI is the latest generation of AI and is still an emerging subject in service applications (Huang & Rust, 2018; Wirtz et al., 2018).

Self-learning and connectivity are two important dimensions of intuitive AI that are so significant in service. Self-learning refers to the machine's ability to improve automatically by experience through various methods such as algorithm-based machine learning, deep learning, and automated machine learning. Connectivity is explained by the progress of communication and internet technology that makes it possible to expand self-learning through the network rather than through a machine. Networked AI leads to the creation of collective intelligence (Huang & Rust, 2018).

AI technologies are capable of storing experiences and learning from those experiences which result in increasing competence over time. It means, through the passage of time, services and products become better and complete and accordingly gain great competitive advantage (Naqvi, 2017). Having such strengths enable AI to change the way organisations offer personalised and customised services within service encounters. AI affects the nature of interactions between customers and frontline employees or organisations to receive or co-create value, and as a result it improves the customer experience. Service encounters are vital constructs that result in service outcomes like customer satisfaction and loyalty or even perceptions of service quality (Ostrom et al., 2019). Service encounters are inevitable components of frontline interactions. Consequently, it is important to investigate using intuitive AI applications (e.g., conversational agents such as chatbots, virtual assistants) as frontline employees. It would help to understand how the customer experience of AI-based organisational frontlines would be similar to, different from, or even superior to, using human frontline employees.

Hence, for understanding the similarities and differences between AI enabled organisational frontlines and those with human frontline employees, it is critical to study service encounters with AI applications such as conversational agents (e.g., chatbots and virtual assistants).

2.4.1 Conversational Agents

Conversational agents are explained as "software that accepts natural language as input and generates natural language as output, engaging in a conversation with the user" (Araujo, 2018, p. 184). Contemporary conversational agents can sustain better conversations relative to former versions due to natural language processing and AI constant progresses (Araujo, 2018).

Personal AI assistants are one kind of conversational agent that are increasingly ubiquitous (Danaher, 2018). Danaher (2018, p. 631) conceptualises a personal AI assistant as "any computer-coded software system/program that can act in a goal-directed manner." These computational programs or AI assistants are designed with anthropomorphic features. Intellectualised anthropomorphism (see section 2.3.2) is applied to these technologies to enhance understanding of these technologies, improve technology acceptance and user competence during interaction with them (Epley et al., 2007; Salles et al., 2020). Almost every smart phone has a personal AI assistant to help users with basic cognitive tasks. Google's Assistant and Apple's Siri are the most common examples. Specific apps present AI assistants for special tasks. However, these AI assistants are in their infancy with the technology continually evolving with increased usage of AI assistants (Danaher, 2018).

AI-assistants (i.e., cognitive computing systems) can "understand our human language, they recognize our behaviours and they fit more seamlessly into our work-life balance. We can talk to them, they will understand our mannerisms, our behaviours and that will shift dramatically how humans and computers interact" (Veres, 2017, p. 1). Nonetheless, AI assistants raise ethical problems and issues related to societal norms in human-machine interactions (Danaher, 2018; Seymour, Riemer, & Kay, 2018).

Marketing literature illustrates that conversational agents (e.g., AI-assistants) are mainly applicable in service encounters (Araujo, 2018). AI-assistants revolutionise the customer experience by interacting with users with natural dialogue (Cheng & Jiang, 2020b). These assistants not only provide instant conversations but also they can enhance the customer experience through the humanlike voice-based interactions (Cheng & Jiang, 2020b; Huang & Rust, 2018). However, with applying intuitive AI these intelligent assistants become more human-like (i.e., anthropomorphism) cognitively and behaviourally (Huang & Rust, 2018). This has consequences for human-to-machine interactions and in turn, the forming and developing relationship between them.

2.4.2 Anthropomorphism

Anthropomorphism is generally defined as "the attribution of distinctively human-like feelings, mental states, and behavioural characteristics to inanimate objects, animals, and in general to natural phenomena and supernatural entities" (Salles et al., 2020, p. 89). Damiano and Dumouchel (2018, p. 2) likewise conceptualise anthropomorphism from a psychological stand point as "a fundamental and permanent dimension of the human mind, rather than an early stage of its cognitive development, that is grounded in neural mechanisms also found in other older species, and which is modulated by individual traits." Anthropomorphism also can go beyond the theory of mind (i.e., ascribing mental life to others) through attributing emotional moods, behavioural features and humanlike shape to the non-human (Epley et al., 2007; Salles et al., 2020). Anthropomorphism in this research refers to the extent to which customers perceived machines as human-like based on a machine's human characteristics or traits.

Anthropomorphism has two dimensions: Mindful and mindless (i.e., conscious and unconscious) anthropomorphism. Mindful anthropomorphism is conscious assessments of whether an entity is human-like or machine-like, while mindless anthropomorphism is attributing human features to an entity (Araujo, 2018).

Anthropomorphism is brought up as a psychological process of inductive reasoning that can meet the need for social connections by facilitating human-nonhuman social interactions (Blut, Wang, Wunderlich, & Brock, 2021). Computers are considered as social actors that humans desire to have social interaction with, similar to humans (even mindfully). The more social cues exhibited by computers, the more users show social reactions (Araujo, 2018). Araujo (2018) suggests that social responses to computer agents may happen spontaneously as an unconscious process in which humans focus on social cues rather than other features of the agent. Moreover, anthropomorphic features are effective in eliciting different behaviours (e.g., making customers feel more comfortable), even under conditions where users are aware of interacting with a technology (Araujo, 2018; Mende, Scott, van Doorn, Grewal, & Shanks, 2019; Qiu, Li, Shu, & Bai, 2020). Even the slightest cues can affect a human's perception of computers, linguistic cues (e.g., language style) and chosen name for technology (e.g., human-like vs. machine-like), impact users to anthropomorphise them (Xu & Lombard, 2017).

Previous research investigated the effects of physical anthropomorphic features on service encounters (Araujo, 2018; Qiu et al., 2020; Wirtz et al., 2018). Araujo (2018) studied anthropomorphic design cues (i.e., human-like language or name), Wirtz et al. (2018) researched human appearance, and Qiu et al. (2020) investigated the effects of imitating physical human behaviour (not cognitive behaviour) by robots on the customer hospitality experience. However, this research focuses on machine's cognitive and behavioural anthropomorphic features.

2.4.3 Anthropomorphism and Relational Factors

Anthropomorphism causes customers to perceive machines as more human-like and sociable, which evokes a stronger sense of social presence and emotional attachment to the machine. Consequently, anthropomorphism makes building rapport easier and more enjoyable (Blut et al., 2021). In addition, attributing human capabilities to nonhuman agents causes customers to believe that the agent is more competent. Thus, customers trust more in human-like machines to deliver a service (Blut et al., 2021). Literature endorses the effects of anthropomorphism on trust. Waytz, Heafner, and Epley (2014) showed that people who anthropomorphised autonomous vehicles trust them more. van Pinxteren, Wetzels, Rüger, Pluymaekers, and Wetzels (2019) found that anthropomorphising service robots builds trust in users. De Visser et al. (2016) proposed anthropomorphism as a remedy for the formation, violation, and repair phases of trust. They identified that anthropomorphic agents lead to superior trust resilience and greater resistance to trust breakdowns. Also, anthropomorphism brings about human-like trust repair behaviour, which eliminates human-machine agent differences (De Visser et al., 2016).

In human-robot relationships, anthropomorphism reduces perceived privacy risk and uncertainty through enhancing the sense of predictability and controllability of a nonhuman agent in interactions (Epley et al., 2007). Benlian et al. (2020) illustrated that when users anthropomorphise smart technologies, they perceive lower privacy invasion. In the service context, the more humanlike customers perceive the machine to be, the more the experience is perceived as safer (Blut et al., 2021).

2.4.4 Anthropomorphism and Customer Engagement

In human-machine relationships, a machine's physical and nonphysical design features and human characteristics are predominant antecedents of anthropomorphism (Waytz et al., 2014). Empirical research has indicated perceived human likeness (i.e., anthropomorphism) enhances the adoption of and engagement with technology. Generally, anthropomorphic features make connecting to technology less inhibited through the creation of unique interaction methods (Pfeuffer, Benlian, Gimpel, & Hinz, 2019).

Anthropomorphism has a positive effect on intention to use technology particularly when customers perceive anthropomorphic features of the technology are similar to themselves (Blut et al., 2021). However, Mori, MacDorman, and Kageki (2012), drawing on the uncanny valley theory, noted that anthropomorphism's effect on the customer's intention to use is not always positive, as humans may perceive highly humanlike technologies as creepy and uncanny. Which can result in a feeling of discomfort and eeriness that leads to rejection.

Anthropomorphic features allow machines to establish a social threshold (i.e., social presence) and make users more inclined to have social interactions with the machine. Highly anthropomorphised machines with strong realism (e.g., behavioural and appearance) can build a sense of social presence even with only behavioural realism and lack of human-like appearance (Damiano & Dumouchel, 2018). Anthropomorphism affects social presence intuitively and directly. It evokes a sense of social presence by giving a person the sense of interacting with another person (Kim, Park, & Sundar, 2013). Therefore, in the service context, anthropomorphic features improve social interaction by giving customers a stronger sense of social presence (Blut et al., 2021).

2.4.5 Anthropomorphism and Customer Service Experience

There are different viewpoints regarding the effect of anthropomorphism on the customer service experience. On the one hand, some scholars believe that the anthropomorphic features of service robots enhance engagement through human-robot social interaction (Novak & Hoffman, 2019). On the other hand, others argue perceived anthropomorphism creates a sense of eeriness and discomfort for humans (Mende et al., 2019). Accordingly, the effects of anthropomorphism on the customer service experience need further investigation. Although, previous research noted various results (e.g., positive, neutral, negative effects) regarding the impact of anthropomorphism on customer intention to use service robots (Blut et al., 2021), it requires more study applying AI and its resulting anthropomorphic features to engage customers more strategically.

Van Doorn et al. (2017) identify a need to research how anthropomorphism affects customer outcomes such as engagement, satisfaction and loyalty. Thus, this research aims to study how intuitive AI and anthropomorphic features resulting from AI affect the customer service experience of AI-based FLEs and forming relationships with them.

Anthropomorphism by design can bring some ethical consequences. Salles et al. (2020) noted that there are concerns about mental manipulation through attributing anthropomorphic features to AI and making them similar to humans. They argued that attributing anthropomorphic features may lead users in a particular decision making direction and make them more vulnerable. Moreover, socialising with agents that are not really social can only temporarily substitute human interaction's richness (Salles et al., 2020). Consequently, despite machine behaviours similar to human behaviours it can be proposed that human interactions are superior.

2.4.6 Machine Behaviour

AI agents have become integrated in human life (Rahwan et al., 2019; Sarma & Hay, 2017). Consideration of an AI agent's behaviour is critical as they can exhibit behaviours and produce societal effects. Intelligent machines can affect human behaviour (e.g., through the way they behave politely) and humans also have effects on creating and developing behaviours of intelligent machines (e.g., by the way they respond to an intelligent assistant's actions, which affects its training through machine learning). Humans inform an intelligent machine's behaviour by direct AI systems engineering, by training these systems with programming, and through passive observations of human behaviours through data (Rahwan et al., 2019). Thus, it can be seen that training intelligent machines through observing human behaviour makes machines more human-like behaviourally over time.

To study machine behaviour, Rahwan et al. (2019) warn researchers about over reliance on anthropomorphism because machines are not humans and behave completely different from humans. Although these methods could be effective in studying machine behaviours, machines may show types of intelligence and behaviours which are qualitatively different from human agents. However, Sarma and Hay (2017) believed that considering anthropomorphic designs (i.e., commonalities with the human mind) which build perceptions of human value alignment is necessary.

Machine behaviour has been investigated in computer science, robotics, and engineering to design and create these machines (Bagde & Petros, 2005; Feddema, Robinett, & Driessen, 2003; Li, Kedous-Lebouc, Foggia, & Mipo, 2010; Rahwan et al., 2019). This research studies machine behaviour considering AI cognition and its effects on human-machine relationships in marketing. For this purpose, human-like manners (i.e., mannerism) are considered in human-to-machine interactions.

Mannerism is often considered as habitual behaviour (Burrell, 1985). Burrell (1985, p. 188) defined mannerism from an ethological viewpoint as "altered forms of ritualised behaviour that serve a communicative purpose". Adopted from Burrell (1985) definition, this research studies mannerism as an accepted way of speaking or behaving based on social and moral norms.

2.4.6.1 Morality and Machines

Human societies cannot exist without norms. Social and moral norms (i.e., morality rules that people follow (Harms & Skyrms, 2008)) form human behaviour in every human society. Therefore, introduced machines to society must behave according to societal norms as well (Malle, Bello, & Scheutz, 2019). Malle and Scheutz (2018, p. 4) defined a machine as moral “if it has one or more relevant competences that people consider important for living in a moral community.”

Researchers have different opinions regarding moral machines (Huang & Rust, 2018; Malle et al., 2019; Wirtz et al., 2018). Wirtz et al. (2018) argued that in human-machine interactions, it is required that machines observe social norms such as exhibiting appropriate behaviour and emotions to have successful interactions. Malle et al. (2019) explained that artificial agents can be designed with the capability of respecting and obeying norms. They mentioned these norms can be taught to machines by instruction and observation. But Huang and Rust (2018) believed at the current level of technology, we cannot attribute a considerable degree of moral autonomy to machines. Machines have progressed in cognitive skills and obtaining human cognitive abilities like planning and rationality. However, human employees are better in affective, social and personal ability (non-cognitive) skills (Belanche, Casaló, Flavián, & Schepers, 2020).

The ubiquity of intelligent machines which meet and exceed human cognitive abilities links AI systems and understanding of human values together. There are diverse factors that may affect human values represented by AI systems, for instance cultural values or ethical norms differ from one society to another (Sarma & Hay, 2017). In this regard, Awad et al. (2018) illustrated that defining a moral machine for all human beings is impossible because different countries have diverse moral preferences based on various cultures and economies. But they mentioned that designers can build broad ethical codes based on universal human values so that machines are perceived as moral and ethical by most humans.

2.4.6.2 Moral Competence

Since autonomous machines undertake social roles more and more in human societies, these machines need to have levels of moral competence to confirm safety, acceptance, and justified trust (Malle & Scheutz, 2018). Malle (2016, p. 243) identified some factors that structure human moral competence, which include: “moral vocabulary; a system of norms; moral cognition and affect; moral decision making and action; moral communication.” They translate these factors for machines to conceptualise machine moral competence:

- *A system of norms* includes standards for behaviour in a community. They lead a machine to behave in a given way (i.e., moral action) and form other people's judgment about that behaviour (i.e., moral judgment).
- *A moral vocabulary* allows the machine to display norms conceptually, linguistically, and morally, along with their proper judgment and supplying communication responding to these (i.e., moral communication).
- *Moral action* is action in accordance with the norms and is therefore compatible with other members of society who act under the same norms.
- *Moral judgment* is the assessment of behaviour toward norms and processing information that leads to special judgment.
- *Moral communication*, often influenced by emotions and feelings, represents the moral judgments of individuals and their efforts to identify, explain, or defend violations of norms, as well as to negotiate or repair social alienation after violations of norms (Malle & Scheutz, 2018).

These factors can help in designing machines that have one or more of these human factors (Malle, 2016).

Machines have to learn various norm systems depending on the communities they are deployed to. Most communities have overlap in norms they follow and machines may be better at following various norm systems of different communities. Thus, they are less biased than humans morally (Malle & Scheutz, 2014).

Affective phenomena mostly accompany moral judgments, but they are not an essential part of those judgments. Thus, if emotions are not necessary, machines, even if they do not have emotions, could be moral (Malle & Scheutz, 2014). Malle (2016) proposed the examination of competences people expect of one another instead of true moral competence. He believed people look for at least some of these competences to form social relationships with social machines. In addition, Malle (2016) argued if robotic design build morally competent robots, those robots could be trustworthy to engage with, when receiving services. Therefore, it is significant to study the effects of intelligent machines, which can display some factors of moral competence in interacting with humans, in AI-based service encounters in customer engagement.

2.5 Review of Customer Service Experience Literature

In the service context, reviewing literature shows that only limited empirical studies investigated all physical, social, cognitive, affective and sensorial dimensions of the customer service experience (Mahr, Stead, & Odekerken-Schröder, 2019). Mahr et al. (2019) did a systematic text mining review to study the conceptual structure of customer service experience. Based on the analysing of customer service experience publications between 2009-2018, their study categorises the customer service experience research into three key areas:

- Servicescape
- Service system architecture
- Outcome measures

Research on servicescape concentrated on interaction (social dimension) and online environments (physical dimensions). In this category interaction highlighted the actor's role and engagement in the servicescape (Mahr et al., 2019). Engagement theory also supports actors' engagement in the servicescape (Li, Juric, & Brodie, 2018). Then, research on service system architecture mostly focused on value (utilitarian, hedonic, and social) and process which is related to systems, technology, innovation, and development. In the next classification, research on outcome measures centred on relationship (affective dimension) and purchase. Sensorial aspects underlined this category of the customer service experience while it is connected to the online environment in the servicescape (Mahr et al., 2019). Also, Mahr et al. (2019) research illustrated that less or no attention has been paid to the cognitive aspect of the customer service experience in the relevant literature. Relying on Mahr et al. (2019) study, this research takes a systemic view towards the customer experience and reviews different dimensions of customer service experience. Moreover, this research takes an inductive/abductive approach in reviewing the body of literature. Initially, the main factors and their fundamental dimensions based on the current literature were expanded to illustrate research gaps and the importance of research questions. Then, after data analysis, literature on newly emerged dimensions of each factor was added to give a better understanding of next chapters.

2.5.1 Customer Engagement

The engagement has been defined differently in diverse contexts. In business, engagement has been titled as a contract (Pansari & Kumar, 2017). In management, engagement is illustrated as the organisational activity with internal stakeholders (Brodie, Hollebeek, Juric, & Ilic, 2011). In marketing literature, it is demonstrated as a customer's activity concerning the organisation and is labelled as customer engagement (Pansari & Kumar, 2017; Vivek, Beatty, & Morgan, 2012). Moreover, customer engagement is defined as the level of a customer's physical, cognitive, and emotional presence in customer-service organisation's relationship (Heinonen, 2018). Generally, engagement is considered as a positive concept relevant to features like "passion, affection, absorption, and dedication" (Heinonen, 2018, p. 150).

Practitioners and academics have different views on customer engagement conceptualisation (Heinonen, 2018; Vivek et al., 2012). Practitioners consider customer engagement from the organisational viewpoint as activities that simplify frequent interactions between customers and frontline employees, which empowers a customer's psychological, physical or emotional investment in a service/product, brand or organisation (Vivek et al., 2012). Whereas, academics in information systems explain customer engagement as the "intensity of customer participation with both representatives of the organisation and with other customers in a collaborative knowledge exchange process" (Vivek et al., 2012, p. 128). According to their view, customer engagement consists of cognitive, emotional, behavioural, and social features (Heinonen, 2018; Vivek et al., 2012). The cognitive and affective factors of customer engagement include the customer's feelings and experiences while the behavioural and social factors are related to gaining the current and potential customer's participation in and outside of the exchange condition (Vivek et al., 2012). In addition, behavioural manifestations are beyond the purchase and a result of motivational drivers (van Doorn et al., 2010).

From a customer viewpoint, the level of engagement can change between positive or negative and can be shown in the contribution of customers in service processes. The negative aspects of engagement (e.g., disengagement) are substantial to build a comprehensive understanding of engagement. Positive engagement is expected to happen with a desirable experience for a customer and similarly when a factor is perceived as undesirable for him/her it is expected to result in negative engagement (Heinonen, 2018).

Similarly, Zhang, Hu, Guo, and Liu (2017, p. 843) conceptualised customer engagement as "a psychological state that emerges during the process of interacting and co-creating customer experience with other stakeholders in a specific service exchange with a focal agent/object, and is manifested in positively valence behaviours of active and consistent interactions". Above all, Pansari and Kumar (2017, p. 295) explained customer engagement as "the mechanism of a customer's value addition to the firm, either through direct or/and indirect contribution".

In a different way, Moliner-Tena, Monferrer-Tirado, and Estrada-Guillen (2019) defined customer engagement from two different approaches, multidimensional and uni-dimensional conception. On the one hand, the multidimensional conception of engagement explains customer engagement as "a psychological state that happens by co-creative and interactive customer experiences with a focal agent or object in main service relationships" (Moliner-Tena et al., 2019, p. 732). On the other hand, the uni-dimensional affective approach defined customer engagement as an individual difference demonstrating a customer's interest to be involved in objects according to a customer's own sense-making (Heinonen, 2018; Moliner-Tena et al., 2019).

Customer engagement contains the connection that individuals build with organisations according to their experiences from an organisation's activities and offerings (Vivek et al., 2012). Furthermore, scholars illustrated that customer engagement, instead of being an objective factor, results from repeated and positive affective interactive experiences among customers and engagement factors (Zhang et al., 2017). Customer engagement is about interactive and co-creative experiences of customers with other stakeholders regarding service relationships like a brand, service/product or organisation (Heinonen, 2018). Customer engagement is created by virtue of interactive experiences. It is the result of frequent interactions (Merrilees, 2016).

Most organisations have been faced with transformation and dynamism due to the progress of technology, growing customer participation in the provision of service, and intense competition resulting from globalisation. Therefore, researchers and practitioners agree that understanding the dynamic nature of customer behaviour is important to preserve and strengthen customer relationships (Heinonen, 2018). Customer relationships would strengthen, fade, or end, because of the interactions between positive and negative perceptions that lead to different customer engagement levels (Bowden, 2009; Heinonen, 2018). As for organisations, they have recently had to concentrate on personalising interactions and understanding the unique challenges of the customers to change their life properly, and involving them as spokespersons of the organisation (Pansari & Kumar, 2017).

Customer engagement displays a new stage in marketing evolution. In which customer emotions are added to the set of influencing behaviours that directly relate to purchasing and other customer behaviours. It goes beyond purchasing and indirectly affects the organisation's business (Moliner-Tena et al., 2019; Pansari & Kumar, 2017).

Components of customer engagement are categorised as antecedents (e.g., ease of use (Heinonen, 2018), trial marketing (Wang, Oh, Wang, & Yuan, 2013), technological sophistication (Weil & Rosen, 1995), privacy risk and uncertainty (Lee, 2019)) and consequences (e.g., WOM (Verhoef, Reinartz, & Krafft, 2010), reuse intention (Choi & Sun, 2016), satisfaction and emotion (Moliner-Tena et al., 2019; Pansari & Kumar, 2017)). However, these antecedents and consequences of customer engagement could change in intuitive AI-based service encounters. Therefore, engagement with human-like machines displaying cognitive, emotional, and behavioural aspects require more investigation. This gap leads us to the first research question:

RQ1: How AI-based organisational frontlines affect customer engagement in service encounters?

2.5.1.1 Antecedents of Customer Engagement

2.5.1.1.1 Enablement

Guo, Zhu, and Chen (2021, p. 1602) conceptualise enablement as "a certain set of preconditions, tools and practices that the firm creates in order to facilitate the involvement of customers." In a marketing context, enablement has been studied as "bundling" (Barrutia Legarreta & Echebarria Miguel, 2004) and "trial marketing" (Wang et al., 2013). Barrutia Legarreta and Echebarria Miguel (2004) conceptualise bundling as “selling of two or more product/service in a single package.” For instance, if you buy a TV from the Amazon company, you will receive a TV and an Amazon Alexa while paying the price of the TV, or you can buy a TV and receive Amazon Alexa for half price. Offering bundles increases the probability of customer satisfaction and desirable behavioural intentions which enhance customer engagement (Hall, Binney, & Vieceli, 2016; Ranaweera & Karjaluoto, 2017). Bundling has been studied in service literature mainly in respect to technology product-service combinations while considering value from bundles to other outcomes (Ranaweera & Karjaluoto, 2017).

In product trials customers receive a real product and experience the product with sensory indicators (e.g., visual, auditory, olfactory, etc) which results in forming their opinion towards the product and brands based on the sensory stimuli (Wang et al., 2013). Consequently even when people receive the product as a gift from their family or friends this could have a similar effect as if they received it as a free sample.

Free trial is one of the marketing stimuli which has been utilised to enhance user acceptance and purchase intention of technology (Wang et al., 2013). It is applied to invite customers to try products before a purchase (Boo, 2020). In addition, a trial operates as an informational function that influences a customer's expectation, demand, and price (Wang et al., 2013). Obtained information through a free trial (i.e., direct experience) leads to changing to the brand of the free trial product and enhancing brand trust (Boo, 2020; Kuzma & Wright, 2015).

2.5.1.1.2 Motivation

Mouakket (2019, p. 102) defined motivation as "a psychological force that drives people to behave in ways that ensure the fulfilment of certain desires." Motivations are classified as both intrinsic and extrinsic (Chaurasia, Verma, & Singh, 2019; Pelletier et al., 1995).

Intrinsic motivations refer to engaging in an activity for the pleasure and satisfaction that results from accomplishing that activity (Chaurasia et al., 2019; Pelletier et al., 1995). Intrinsic motivations are derived from an individual's psychological innate needs of competence and self-determination (Pelletier et al., 1995). The intrinsically motivated individual engages in an action voluntarily and in the absence of physical reward or external restrictions (Pelletier et al., 1995). Intrinsic motivations arise from an understanding of the activity. In contrast, extrinsic motivations are concluded from instrumental outcomes (Chaurasia et al., 2019).

Extrinsic motivations are an understanding of accomplishing an activity by users to gain specific goals or rewards (Chaurasia et al., 2019). Extrinsic motivations relate to engaging in an activity as a means to achieve an aim and not for the activity itself. In addition, extrinsic motivations pertain to behaviours which are provoked by external contingencies (Pelletier et al., 1995).

Motivations are identified as the main driver of technology usage, since they cause behaviour to lead towards specific goals (Chaurasia et al., 2019). Chopra (2019) studied customers' motivations to use AI-technologies (e.g., chatbots and voice assistants) for shopping and saw that a customer's motivation to engage with AI-technology is mostly an intrinsic motivation, which could be a result of habit or passion for technology. He believed that by following intrinsic motivation, some incentives (e.g., time or convenience) motivate customers extrinsically to use AI-technology (Chopra, 2019).

2.5.1.1.3 Technological Sophistication

Technological sophistication influences ease of use and empowerment regarding user engagement with technology (Fan et al., 2017; Ghorab, 1997; Obi, Leggett, & Harris, 2017; Rousseva, 2008; Weil & Rosen, 1995). Technological sophistication is particularly important in utilising innovative and new technologies (Cavaco & Machado, 2015). Weil and Rosen (1995) examined technological sophistication as the use of consumer technology. They assessed technological sophistication as "a function of the availability and utilisation of home technology, university technology, and consumer technology" (Weil & Rosen, 1995, p. 98). To recognise the reasons why customers utilise technology, previous research mostly used the technology acceptance model (Ghorab, 1997). According to the technology acceptance model, perceived ease of use is one of the effective factors for users' attitudes towards technology usage, which is a key determinant of a user's behaviour to utilise the technology (Ramirez-Correa et al., 2019).

Fan et al. (2017) studied technology utilisation from a user's active engagement status, a different way from the technology acceptance model. They suggested dependence on the technology arises from a user's active engagement with technology and introduce it as an effective factor regarding a user's technology utilisation. Technology dependence refers to the reliance on a variety of devices, software applications, and tools to perform specific functions (Fan et al., 2017). One of the motives behind an individual's dependence on the technology is enabling empowerment (Obi et al., 2017).

2.5.1.1.4 Ease of Use

Wang et al. (2013, p. 197) conceptualised ease of use in the technology context as “the extent to which a technology is perceived as being easy to understand and use.” Perceived ease of use also is considered as the degree to which an individual believes using a specific system is effortless (Ramirez-Correa et al., 2019). Ease of use has been studied mostly in a technology context from the technology acceptance model point of view, and is recognised as a determinant of a user’s attitude and behavioural intention to accept and apply a technology (Ramirez-Correa et al., 2019; Wang et al., 2013; Yang, Al Mamun, Mohiuddin, Nawi, & Zainol, 2021).

Perceived ease of use has a significant effect on intention to reuse the technology (Ramirez-Correa et al., 2019). Moreover, perceived ease of use increases perceived usefulness that also leads to enhancing intention to use the technology (Huang, 2021). Consequently, perceived ease of use has a significant effect on engagement and continued technology usage (Heinonen, 2018; Wang et al., 2013).

Blut et al. (2021, p. 7) noted that “with few exceptions (Wirtz et al., 2018), ease of use has not been examined in robot studies.” However literature suggests that anthropomorphism causes robots to be perceived as more humanlike and familiar. Familiarity facilitates learning how to use and interact with robots. Also, anthropomorphism makes interactions more natural. Hence, the perceived ease of use will be increased (Blut et al., 2021).

2.5.1.1.5 Empowerment

Empowerment has been conceptualised in the behavioural and social sciences with different definitions (Pires, Stanton, & Rita, 2006). It can refer to either a process, or an outcome, or both. Empowerment as a process is a mechanism enables individuals take control over issues while as an output empowered individuals “would be expected to feel a sense of control, understand their socio-political environment, and become active in efforts to exert control” (Pires et al., 2006, p. 938).

The term "empower" means giving a person power which refers to "authority in a legal sense, capacity and energy" (Berraies, Chtioui, & Chaher, 2019, p. 1835). Technological empowerment facilitates interactions between two parties in an information technology domain

(Wang, 2008). This ability distinguishes firms from one another in interacting with individual customers (Chih, Huang, & Yang, 2016).

Customer empowerment is the innovation of technological knowledge in online environments (Chih et al., 2016). It includes giving the opportunity to customers to select what they want in the time they want and based on their terms (Pires et al., 2006). Moreover, customer empowerment illustrates "firm initiative or the extent to which firms provide customers with technological avenues through which to connect and collaborate with these firms and other customers" (Chih et al., 2016, p. 104). Consequently, customer empowerment enhances customer engagement through facilitating customers' interactions with firms and other customers (Chih et al., 2016).

2.5.1.1.6 Perceived Privacy Risk and Uncertainty

Perceived level of danger entailed in interacting with a machine refers to perception of risk and privacy invasion (Blut et al., 2021). Privacy invasion is an “individual’s perception that their privacy has been compromised, making it theoretically the most adequate stressor to capture fit or misfit between the demands of intrusive technology features and the privacy needs of users” (Benlian et al., 2020, p. 1014). In human-to-machine interactions, technological artefacts could provoke and enhance perceived privacy invasion, as they are realised to be artificial and impersonal (Benlian et al., 2020).

Uncertainties and concerns have been growing in online environments and have become the main preventive to adopt and apply the technology and its related products or services (Lee, 2019). For example, the unintentional voice activation feature of home personal assistants is considered as privacy invasion by users. This subject is identified as the main privacy concern for users, that they feel service providers intrude on their private life which causes their engagement with technology to be affected (Benlian et al., 2020). Perceived privacy risk and uncertainty are categorised among diverse risks that negatively influence online behaviour intentions (e.g., intention to use) (Lee, 2019).

Previous research propounded the interplay between technology-driven privacy invasion and potential capacities of anthropomorphic design features (e.g., face or body) to deal with it (Benlian et al., 2020; Epley et al., 2007). For instance, Benlian et al. (2020) illustrated that users of smart home assistants felt a lower level of privacy invasion with anthropomorphised technology. Consequently, in AI-based service encounters it can be said that the more humanlike perceived AI-assistant, the safer interactions experienced by customers. However, the effects of cognitive and behavioural anthropomorphic features on perceived privacy risk and uncertainty due to making machines more humanlike need more investigation.

2.5.1.2 Consequences of Customer Engagement

2.5.1.2.1 Word-of-Mouth

Word-of-mouth (WOM) is defined as "dynamic and on-going information transmitted via person-to-person direct interaction regarding the ownership, impressions, or recommendations of specified products, services, and sellers" (Pang, 2021, p. 3). It is an oral communication between two people: sender and receiver (Abrantes et al., 2013).

Since WOM affects customers' attitudes, beliefs, behavioural patterns and purchase decisions, it has been considered as a key force in the market (Abrantes et al., 2013). Generated information by customers according to their personal experience (i.e., WOM) influences other's attitudes more than generated information by companies (e.g., advertisement) (Abrantes et al., 2013).

Positive WOM generates advantageous information regarding the service or product for customers, and through that facilitates the promotion of the product or service (Lien & Cao, 2014). Sweeney, Payne, Frow, and Liu (2020, p. 146) considered WOM as an interpersonal communication, in which five types of motivation can lead to transferring WOM: "impression management, persuasion of others, emotion regulation, social bonding, and information acquisition". These motivations propose the creation of emotional expression of endorsement. Endorsement refers to greatly influential communication that is formed with the explicit aim of affecting others. It is a specific form of positive WOM which can significantly impact purchase behaviour (Sweeney et al., 2020).

Perceived service value (i.e., utilitarian and hedonic) positively influence post-consumption outcomes such as of WOM and satisfaction (Babin, Laroche, Lee, Kim, & Griffin, 2005). In the human-machine relationship, through applying use and gratification approach, hedonic and utilitarian value have been recognised as key motivations of new media users to spread WOM.

Perceived value via affective experiences influence a user's attitude and behaviour which can be significant in WOM engagement (Pang, 2021).

2.5.1.2.2 Social Presence

Social presence is the extent to which a person believes in the presence of someone else (Blut et al., 2021). It is "the feeling that another being (living or synthetic) also exist in the world and appear to react to you" (Araujo, 2018, p. 184). Van Doorn et al. (2017, p. 44) define social presence in human-robot interaction as "the extent to which machines (e.g., robots) make consumers feel that they are in the company of another social entity." Social presence has been defined from two perspectives. First, it is defined as "co-presence", a sense of being with another person in the same place. Second, it is also defined as being psychologically involved with another human being (Lazard, Brennen, Troutman Adams, & Love, 2020).

Social presence can gratify the sociality needs (Epley et al., 2007). Therefore it can be an affective engagement factor for those who need superior interaction (Araujo, 2018). Literature argues that social presence affects a customer's perception of technology in the way that they are engaging and interacting with technology as a real social entity (Araujo, 2018; Xu & Lombard, 2017). Anthropomorphic features allow machines to reach a social threshold (i.e., social presence) and make users more inclined to have social interaction with the machine. Highly anthropomorphised machines with strong realism (e.g., behavioural and appearance) can build a sense of social presence even with only behavioural realism and lack of human-like appearance (Damiano & Dumouchel, 2018).

People who have a strong sense of social presence form more positive perceptions towards a machine due to attributing them human features and consider them as an artificial social actor (Kim et al., 2013). A perceived sense of social presence due to anthropomorphic features (e.g., human appearance, human characteristics, or imitating human behaviour) facilitates human-machine interactions (Blut et al., 2021). Therefore, in a service context, anthropomorphic features can deliver a stronger sense of social presence to customers, which means improving social interaction.

A sense of social presence enriches socio-emotional experiences of users in machine-mediated interactions (Kim et al., 2013). A sense of social presence influences the user's perception regarding the feeling of sociability and human warmth in AI-based interfaces (Han & Yang, 2018), usefulness and trust (Lazard et al., 2020), and affect users' behavioural intention or actual use of machines (Xu et al., 2012).

2.5.1.2.3 Reuse Intention

Cheng and Jiang (2020b, p. 7) referred to intention as "an individual's subjective probability that he/she will perform an actual behaviour." Thus, reuse intention refers to the probability of a customer's preference to use a product or service again. It indicates subjective preference of customers to use a particular service and recommending that to others (Choi & Sun, 2016).

Previous studies considered different determinants of continuous decisions to use a service or purchase a product, including individual traits (e.g., customers' perceptions of outcome, trust), contextual factors (e.g., previous experiences), and online environment (website interface) (Benlian, Titah, & Hess, 2012; Chou & Hsu, 2016; Zhao, Lu, Zhang, & Chau, 2012).

The former use and gratification literature has studied user intentions of continued use and its relationship with user satisfaction (Cheng & Jiang, 2020b; Papacharissi & Rubin, 2000). Zhou, Fang, Vogel, Jin, and Zhang (2012) investigated the continuance intention of social virtual world services for users and the resulting utilitarian and hedonic value, that through affecting satisfaction influences the continuance intention. They also showed that a customer's perceived utilitarian value by influencing affective commitment (desire-based attachment in the relationship with service provider) increases the continuance intention. By considering the social ability of AI technologies (e.g., socially interact with users directly and not as a medium), the social value effects on reuse intention of the technology need to be studied.

2.5.2 Use and Gratification

Use and gratification literature shows that, in the past decades, scholars focused on the diverse motivations that humans have had for engaging with previous or new media. Based on the use and gratification approach, individuals intend to apply new emerging technologies as they believe that a specific media can address what they need. Hence, they become motivated to use the media to seek different kinds of gratifications (Cheng & Jiang, 2020a; Ji & Fu, 2013).

Current use and gratification literature illustrates that motivations for using new technologies are categorised into three main groups: 1) utilitarian gratification, 2) hedonic gratification, 3) social gratification (Brandtzaeg & Følstad, 2017; Cheng & Jiang, 2020a).

2.5.2.1 Utilitarian Gratification

Utilitarian gratifications are classified as cognitive reactions (i.e., intellectual coping responses that arise from the feedback of a mental process) (Qin, Peak, & Prybutok, 2021). It refers to addressing utility needs of humans like information seeking (Cheng & Jiang, 2020b). Utilitarian gratifications contain utilities that users look for from a media, which is an instrumental gratification (Cheng & Jiang, 2020a).

This type of gratification refers to utilitarian value that a media can provide for a user. Utilitarian value is related to efficient, outcome-driven, and economic objectives when using highly customised services. Utilitarian value mostly refers to cognitive aspects of human perception (e.g., efficiency and convenience) (Pang, 2021).

A user's cognitive experiences (i.e., utilitarian gratifications) affect consumer intention to continuously use the media (Qin et al., 2021). For instance, utilitarian gratification facilitates information seeking needs by the medium, where the information can be transferred in the form of text, picture or video, which leads to enhancing reuse intention (Cheng & Jiang, 2020b).

2.5.2.2 Hedonic Gratification

Hedonic gratifications imply that perceived gratifications are for fun or pleasure (Cheng & Jiang, 2020a). This type of gratification goes back to the entertainment construct of use and gratification theory that refers to the extent to which a media gives hedonic value to a user (Chavez et al., 2020). Hedonic value is usually related to a user's multi-sensory affective experience of services (Pang, 2021). Hedonic gratifications are classified as affective reactions (i.e., emotional coping responses that arise from the user's interaction with technology) (Qin et al., 2021). Users can gain hedonic gratification for entertainment or enjoyment of achieving emotional support (Cheng & Jiang, 2020b).

Hedonic gratifications are recognised as a typical motivation that defines a user's behaviour on social media; for instance, people interacting with other people by online chatting and receiving enjoyment on WeChat (Cheng & Jiang, 2020a). According to the use and gratification approach, consumers use social media for fun, killing time, and spontaneity (Chavez et al., 2020).

Hedonic gratifications facilitate word of mouth behaviour (Chavez et al., 2020). When users have enjoyed a personal experience they are more willing to spread positive WOM (Abrantes et al., 2013). Also, hedonic gratifications positively influence a media user's continuing intention to use the media (Jang & Liu, 2019).

2.5.2.3 Social Gratification

Social gratifications are the human satisfaction of fulfiling communication needs with others (Ji & Fu, 2013). This type of gratification is the social construct of the use and gratification theory that refers to the extent to which a media assists users to "express their personalities, gain peer-support, and develop a sense of belonging to a group of friends, family, and society, substituting real-life partnerships" (Chavez et al., 2020, p. 4). In the technology context, social gratification is defined as "a unique category in enhancing interactions between media users and others" (Cheng & Jiang, 2020b, p. 5).

Researchers considered different dimensions for social gratification. Cheng and Jiang (2020a, p. 341) considered social gratification as "the type of gratifications for social interaction and social presence." Mouakket (2019, p. 103) introduced social gratification dimensions as "social affiliation, pressure, self-concept and interaction." Xu et al. (2012) illustrated social presence as a social gratification that facilitates social interactions. They believed that people use a media to create a sense of connecting with other humans.

Jang and Liu (2019) argued that social gratifications in augmented reality online games and the resulting social gratifications do not have significant effects on a player's continuance use intention. They found that social gratification, only in a certain group of players, may affect continuance use intention. However, Cheng and Jiang (2020a) found that social gratifications facilitate people's intention to reuse social media tools.

Online technologies are used as social platforms where users can interact socially with other individuals. Hence, social interaction is a substantial part of these technologies that fulfils a user's social gratification (Mouakket, 2019). Gratification can be obtained by an electronic communication medium (i.e., internet) through socialisation (Abrantes et al., 2013). While new smart technologies are able to interact with users in humanlike speech, there is a need to investigate how social interaction with these technologies, as one of the interaction parties and not as a medium, changes perceived social gratification by users. This leads us to the second research question:

RQ2: How intuitive AI-based organisational frontlines affect perceived gratification by customers in service encounters?

2.5.2.4 Gratification and Affinity

Affinity illustrates the user attachment to a specific media or content that media transfers (Ji & Fu, 2013; Papacharissi & Rubin, 2000). In particular, media affinity reflects the attachment and importance given to the method of content delivery or situations of media use (Ji & Fu, 2013).

People can obtain gratification from a special type of content (e.g., information), content delivery method by a technology (e.g., convenience), or the situations of media use (e.g., opportunities for social interaction), which affect affinity through creating a positive attitude towards a media or content. Accordingly, it can be said that behavioural motivation influences attitudes to objects that individuals are involved in. Individuals with higher affinity, talk more often about received content with others, use media more, and engage in para-social interactions (Ji & Fu, 2013).

2.5.2.4.1 Emotional Affinity

Different expressions have been applied to illustrate close human-technology relationships (e.g., intimacy, emotional attachment, emotional affinity, and affective quality) (Matsumaru & Terasawa, 2001; Sung, Guo, Grinter, & Christensen, 2007). Intimate human-machine relationships include at least one of cognitive closeness, physical closeness to technology, and intimacy between individuals mediated by technology (Sung et al., 2007).

Matsumaru and Terasawa (2001) defined emotional affinity in human-robot relationships as a human's positive impression and positive emotions towards a robot. Positive emotions can be generated through design and appearance or easy communication between human and robot

(Matsumaru & Terasawa, 2001). One type of affection that humans can express to robots is attributing anthropomorphic or zoomorphic features to them (Sung et al., 2007).

Jun (2021) suggested that machines which can imitate humans could facilitate intimacy between human and machine. Emotional affinity (i.e., intimacy) can enhance technology adoptation and decrease unreliability in human-machine relationships (Sung et al., 2007).

2.5.3 Business-to-Customers Relationships

Customer relationships have been identified as one of the most essential factors of marketing strategy (Alhathal, Sharma, & Kingshott, 2019; Morgan & Hunt, 1994). The richness of the literature dedicated to relationship marketing illustrates the importance of strengthening customer relationships to enhance the customer experience and gain long-term profitability (Alhathal et al., 2019; Karyose, Astuti, & Ferdiansjah, 2017; Morgan & Hunt, 1994; Yang & Chao, 2017). However, using online platforms (e.g., mobile and websites) have changed the underlying dynamics of service relationships with customers (Alhathal et al., 2019).

Relationship marketing literature illustrates that in order for organisations to preserve their customers they need to persistently maintain and nurture the relationship (Bowden, Gabbott, & Naumann, 2015). In technology-based service encounters, in which technology is part of service delivery process, literature suggested that providers need to meet their customers face-to-face simultaneously to build rapport and decrease negative effects (e.g., service separation: separation between the service provider and customers) of these service encounters (Hartley & Green, 2017). This process helps organisations to gain customer loyalty and commitment (Alhathal et al., 2019).

Customer relationships in face-to-face service encounters are essentially interactive and result in economic and social benefits (e.g., confidence), in which social benefits are effectual in building and maintaining prosperous customer relationships through enhancing interpersonal communication with the employees (Alhathal et al., 2019; Ashnai, Henneberg, Naude, & Francescucci, 2016).

Social benefits develop customer relationships due to creating a sense of familiarity, friendship, rapport, and social support. These social exchange dimensions can lead to building long-lasting relationships between customers and employees, and can help the formation of relational trust and affective commitment in human employee-customer relationships (Alhathal et al., 2019; Hennig-Thurau, Gwinner, & Gremler, 2002). Alhathal et al. (2019) studied familiarity, personal recognition and friendship (i.e., social benefits of customer relationships) effects on building relational trust and affective commitment for users of online or phone banking. The resulting social benefits affected relational trust and affective commitment positively. They applied technology as a technological medium for human-to-human interactions. Therefore, it could be rewarding to investigate social benefits in the human-machine relationship directly.

Customer relationships that contain customer-frontline employees face-to-face interactions (i.e., personalised interactions) could lead to the formation of mutual trust and commitment (Alhathal et al., 2019). Given the significance of relationship marketing and the ubiquity of intelligent online interfaces there is a clear need to investigate the voice-based human-to-machine interaction effects on forming trust and commitment in AI-based service encounters. Especially for those businesses who rely on face-to-face interactions because of its social benefits. Moreover, in a service context, to the author's knowledge, there are no studies that investigate the effects of an intelligent machine's cognitive and behavioural anthropomorphic features on forming relationships between human and machine as one of the relationship parties directly, as opposed to a medium. This gap is important to address, since firstly it helps organisations to have better a understanding of customer experiences across different channels, and secondly it can help organisations to develop their organisational frontlines and attain competitive advantage in service delivery. This leads to the third research question:

RQ3: How does intuitive AI-based organisational frontlines affect human-machine relationships in service encounters?

2.5.3.1 Customer-Employee Social Exchange Relationship

The customer-employee exchange relationship is recognised as a part of the social exchange process in service marketing (Kim & Qu, 2020). Social exchanges indicate a more supported relationship which is based on exchanges for unidentified privileges and benefits over a long period of time (Colquitt, Baer, Long, & Halvorsen-Ganepola, 2014). Both customers and employees play a vital role in the social exchange process (Kim & Qu, 2020; Ma & Qu, 2011).

One of the social exchange relationship's outcomes is employees' prosocial behaviours. Prosocial behaviour is defined as employees' positive behaviours towards customers and that have a significant effect on service evaluation by customers (Cheng & Chen, 2017). It can result in forming trust, affective commitment, perceived support and exchange quality (Colquitt et al., 2014). Besides, customers behaviour and attitudes can affect an employee's prosocial behaviours in service encounters (Kim & Qu, 2020). For instance, an angry customer can influence an employee's response to a customer request. However, with AI-based frontline employees, it could be different.

Social psychology literature argues emotions are a determinant factor regarding fulfiling social exchange in the customer-employee relationship. Emotions help to build and raise social relationships through inspiring reciprocal and prosocial behaviour (Cheng & Chen, 2017; Kim & Qu, 2020). Though in the case of applying AI-based frontline employees in service encounters, how emotions would be defined, formed and developed needs more investigation, particularly when machines are human-like.

2.5.3.2 Trust

Trust is a multi-disciplinary concept that borrows ideas from psychology, economics, sociology, marketing, organisational behaviour, strategy, information systems, and decision sciences (Mukherjee & Nath, 2007). It is a complicated concept and has various meanings in diverse fields. Consequently, various disciplines use different explanations to define it (Chan & Yao, 2018; Ekman, Johansson, & Sochor, 2018; Hsu et al., 2017; Mukherjee & Nath, 2007). Trust is considered as a belief that compounds integrity, competence, and benevolence (Hsu et al., 2017; Kini & Choobineh, 1998; Siau & Wang, 2018), or one party's tendency to depend on another in a situation that has uncertainty and risk (trusting intention), or a compound of these components (Siau & Wang, 2018; Truong, Lee, Askwith, & Lee, 2017). As an attitude trust is "an agent (who) will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Ekman et al., 2018, p. 96).

Some disciplines consider trust as the willingness to operate or a consequence of an action, and others interpret it as another agent's expectation (Selis, 2017). Similarly, trust is also pointed to as a belief that one party will behave conforming to a set of accepted rules and accordingly meet another one's expectations (Selis, 2017; Siau & Wang, 2018). Moreover, trust can be demonstrated as a triad of three opinions: belief, disbelief, and uncertainty, which show the contingency of trusting, distrusting or having doubt about whether to trust an entity or not (Selis, 2017). According to Massey, Wang, and Kyngdon (2019) viewpoint, trust is relevant to the honest and cooperative behavioural expectancy of future actions of another party. Trust is a created expectation in society regarding collective, sincere, and regular behaviour relying on common norms from the part of society members (Massey et al., 2019). Likewise, trust is a belief that the trustee will accomplish the expectations of the trustor without exploiting an individual's or organisation's vulnerabilities, which relies on the competence, integrity, and benevolence of the trustee (Liu, Xiao, Lim, & Tan, 2017). From a psychological viewpoint, trust causes an individual to be willing to be vulnerable towards another party and presumes desirable outcomes of others' behaviours (Hsu, Chen, & Kumar, 2018; Mukherjee & Nath, 2007).

Following on, trust is a multifaceted concept which is affected by participants and environmental factors. It is a psychological evaluation, helping the trustor to make a decision whether to put himself/herself/itself in an uncertain condition in which the trustee may be inappropriate. In computer science, trust has been defined as the belief of a trustor with a trustee that the trustee will prepare or fulfil the aim of trust as trustor's prospect in a particular context for a determined time duration, in which trustors and trustees can each be human, device, machine, applications or services (Truong et al., 2017).

Trust, in the exchange environment, refers to the confidence of the person in the reliability and integrity of another party (Hsu et al., 2017; Morgan & Hunt, 1994). It is presumed that trust plays a significant role in exchange especially in a virtual environment (Hsu et al., 2017). According to Morgan and Hunt (1994) trust exists when one party is confident in the reliability and integrity of an exchange partner. Trust also has a direct relationship with reciprocal behaviour (Hsu et al., 2017). It handles risks and diminishes uncertainty by informal mechanisms in individuals (Guo, Lumineau, & Lewicki, 2017).

In general, trust points to a mental contingency which is created by the individual's evaluation of another party to do a particular action (Tsai & Hung, 2019). Trust is an initial driving force to maintain further interactions which need to be accepted as a standard (Selis, 2017) and it has a very fragile structure that takes a long time to be created but can be ruined very fast (Rehman, Cao, & Gao, 2017).

In complicated technological environments, trust is considered as the main reason for acceptance of the technology. Likewise, it can describe a person's interaction with technology (Siau & Wang, 2018). In such environments trust can be explained as a presumption regarding the expected quality or reliability of a resource according to available information or previous experiences (Fouladi & Navimipour, 2017).

Trust applies to different levels of interaction in agent societies (i.e., where agents are machines or humans), and consist of human-to-human, human-to-machine, and machine-to-machine interactions (Liu, Loper, Ozkaya, Yasar, & Yigitoglu, 2016). Trust is a vital component for any kind of relationship, from human-human relationship to relationships between virtual team members (Siau & Wang, 2018).

2.5.3.2.1 Human-to-Human Trust

Interpersonal trust, namely trust amongst people, according to the theory and evidence, is composed of two major components: cognitive and affective (Guinot, Chiva, & Roca-Puig, 2014; Massey et al., 2019; Tsai & Hung, 2019). Cognitive-based trust is a logical/rational type of trust which is based on the previous evidence of a trustee's reliability and competence regarding their work. In addition, cognitive trust is taken from the belief that another party is trustworthy, reliable, responsible, and competent (Guinot et al., 2014).

In contrast, affective-based trust includes emotional bonds which are created due to reciprocal interpersonal care and concern about the other's welfare, subjective emotions about being secure, not being exploited, and the confidence that the other party will act in favour of the other's interests (Guinot et al., 2014; Massey et al., 2019; Tsai & Hung, 2019). An emotional attachment among a trustor and a trustee is the foundation for building affective trust. In addition, affective trust develops a sense of reciprocity in the relationship that reduces deception (Tsai & Hung, 2019).

Interpersonal trust can also be explained as an individual's perception and psychological mood by which the other party is recognised to be reliable (Li, Wang, & Zhao, 2018) or as a belief that others will not want, in a worst case scenario, to knowingly or intentionally damage you, and in an ideal situation they act in your favour (Ervasti, Kouvo, & Venetoklis, 2019). Plus interpersonal or generalised trust, also known as social trust, illustrates to what extent people believe in others, mainly in people they do not know (Ervasti et al., 2019).

Trust is a criterion for sharing knowledge between individuals and is expanded over time by repeating interactions. As a dynamic and time-consuming procedure, developing it needs initial trust formation and frequent experiment (Hsu et al., 2017; Massey et al., 2019). Moreover, interpersonal trust described as the inclination of a trustor to be vulnerable against a trustee's action, relies on the expectation that the trustee will fulfil a special action for the trustor, without considering the ability of monitoring or controlling (Massey et al., 2019; Tsai & Hung, 2019). High levels of interpersonal trust show that both the trustor and trustee care about each other, listen to problems, cooperate to solve them and provided feedback. It illustrates they are more willing to keep up with each other, help each other and work together constructively (Guinot et al., 2014).

In relationship marketing, trust in the salesperson will affect the future choice and actions of the buyer. Interpersonal trust with customers explains how customers are recognised by organisations to be reliable, as they provide organisations with confidence as a benefit (e.g., knowledge and experience, commitment, and loyalty). In addition, interpersonal trust with customers leads to a relationship with innovation via learning from the customer; as they provide tacit knowledge to improve innovation. It also helps organisations address governance inflexibility drawbacks (e.g., contracts) in turbulent environments (M. Li et al., 2018).

In a B2B context, interpersonal trust between contact people will result in stronger collaboration between organisations and gaining knowledge from each other. On the one hand, it facilitates the transformation and acquiring of external knowledge to expand innovative ideas and practice. On the other hand, it brings up support and reciprocal behaviour that fosters novel ideas and operational support for product innovation. Moreover, interpersonal trust with customers in B2B contexts simplifies cooperative learning, and motivates organisations to combine their resources for handling a complex situation and utilise opportunities in an uncertain and dynamic market (M. Li et al., 2018).

2.5.3.2.2 Human-to-Machine Trust

Having a holistic perspective of trust demonstrates how it is a dynamic process which begins before the first contact of a user with a machine and will extend afterwards (Ekman et al., 2018). Trust is so important to establish willingness for engaging with a machine, using a machine, and ensuring the correct use of that machine. It also is a leading factor of human-to-machine interactions (Ekman et al., 2018; Kini & Choobineh, 1998). Due to the lack of machine ethics (e.g., moral dimension), trust may show an understanding of the features of the technology rather than its motives and/or ethical decision making. An important matter for the user is whether a machine has features that could equip it to complete a promised task or not (Harwood & Garry, 2017).

Substantial features to build interpersonal trust are competence, benevolence, and integrity, that can be interpreted as "the possibility to observe the system's behaviour (performance), understand the intended use of the system (purpose), and understand how it makes its decisions (process)" (Ekman et al., 2018, p. 96).

Competence as a feature is linked often to "experience" and "expertise" and for a machine indicates the capacity of obtaining a result (Harwood & Garry, 2017). Experiences with the system affect trust in the machine based on the continuum of expectation, predictability, dependability, and faith. The predictability of a machine in the initial stages of interaction is recognised by evaluating the consistency of its regular behaviour. As the experience with the system increases, the human-machine trust will be based on the attribution of a dependable feature according to previous experience. The last stage of trust in a system is developing faith which means believing in the dependability of the system's future behaviour (Kini & Choobineh, 1998).

Reputation and/or previous experiences with similar machines or technology affects trust formation even before having personal experience or personal interaction with a machine. Information about or from the machine and past experiences are the main components of trust as an attitude. In addition, users form different levels of trust based on information, impressions, and experiences that result in various intentions on whether to rely on the machine or not. These intentions may become behaviour in the future (Ekman et al., 2018).

Since personal characteristics and knowledge are the bases for a person's trust, providing information regarding systems can be a significant factor to enhance trust in the system. Also, previous research shows that the technical competence and dependability of automation mainly influences trust (Kini & Choobineh, 1998). Dependability is the main feature of the machine to guarantee its functional behaviour and it reflects the degree of the user's trust in the machine's ability to convert the input to output over time consistently (Boucerredj & Debbache, 2018).

According to Kini and Choobineh (1998, p. 9), trusting a machine is defined as "an individual's belief in the competence, dependability, and security of the system under conditions of risk", and it is affected by a person's opinion about specific features of a system. It influences a person's attitude to engage with the machine (Kini & Choobineh, 1998). Trust is essential for automated machines because of the risks and uncertainties they bring with them. Also, it is required to enhance the acceptance of a machine which is a prerequisite to using it (Ekman et al., 2018; Harwood & Garry, 2017).

Ekman et al. (2018) argues that trust in human-machine relationships can be explained in that trust in the machine is shaped according to the perception of the user of a machine, rather than the real trustworthiness of the machine. Therefore, anthropomorphising the machine may help to build and enhance trust (Blut et al., 2021). Previous literature confirms the positive effect of anthropomorphism on trust (De Visser et al., 2016; van Pinxteren et al., 2019; Waytz et al., 2014). All of this research has studied the physical anthropomorphic features (e.g., Humanlike face or body) effects on trust, while the cognitive and behavioural anthropomorphic features effects on forming trust in the human-machine relationship needs to be investigated.

2.5.3.2.3 Machine-to-Machine Trust

Machine-to-machine interactions are the most well-known application form of the 'Internet of Things' within contemporary technology (Hongsong, Zhongchuan, & Dongyan, 2011; Liu et al., 2016). In this type of interaction transmission of data is done by electronic and digital devices such as cable, mobile or wireless technology, which creates important security vulnerabilities, uncertainty, and risks (Hongsong et al., 2011). The Internet of Things (IoT) is a computing concept which describes enabling physical objects to be connected, tracked, coordinated or controlled by using Internet technology and the ability to transfer data over a network without requiring human-to-human or human-to-computer interactions (Liu et al., 2016; Selis, 2017).

In machine-to-machine interactions, since actions take place without human intervention, trust is crucial in creating a seamless connection, safe systems and dependable services (Truong et al., 2017). Also, as remote interactions between machines without a human operator is at risk of being hacked by criminals or of being infected by computer viruses or attackers, trust has been recognised as an efficient counteraction for secure machine-to-machine interactions (Liu et al., 2016).

Machine-to-machine interactions are used to share or exchange information. Trust plays a significant role in these types of interactions, since a machine needs a mechanism to uniquely recognise another machine without human intervention. Moreover, machine-to-machine interaction explains the type of interaction that enables machines to autonomously interact with each other without human intervention. It allows machines to collect data from the real world and applications (Selis, 2017). Both objective and subjective factors from participators and environmental characteristics in machine-to-machine interactions affect trust interactions from social and computer science perspectives. The first version of trust in computer science is system and data security, which encompasses concepts of software, hardware, and communications. The last versions include dependability, reliability, security, and privacy considerations. Therefore, dependability is the genuine feature of the system, and shows the system's capability to deliver services with high quality and securely (Truong et al., 2017).

Trust is a multifaceted subject and plays different roles in different contexts (Liu et al., 2016). Its primary definition is rooted in human-to-human interactions, and then it has expanded to machine-to-machine interactions. In a network, similar to human society, there are various ways to establish trust in relationships between entities. Trust in a relationship can be described as a collection of features regarding the relationship that explains trust in another party (Selis, 2017).

One method to create machine-to-machine trust is using reputation mechanisms based on interactions and feedback ratings of the interactions. Reputation-based machine-to-machine trust frameworks (i.e., machine-to-machine trust) facilitate a network of machines to fulfil a cooperative task with high reliability and high quality (Liu et al., 2016).

Machine-to-machine trust is significant from two aspects:

(1) It applies machine-to-machine interaction experiences in order to create direct trust between two machines. In this regard, feedback ratings and transactional services could be considered as interactions.
(2) Utilising a trust propagation kernel to address the problem of rating weaknesses and cold start problems with a feedback rating based on trust computation (Liu et al., 2016).

Associated with machine-to-machine communications, trust is affected by using secure servers with a certificate. Nonetheless, this is not sufficient because of hackers. According to the trust management framework, there is a trust computation that can be applied mathematically for evaluating trust by machines in a network (Selis, 2017).

Trust computations are composed of five key sections:

1. Trust composition

Trust metrics are key components of trust computation when building trust. They comprise information which is gained from observing entities' behaviour to distinguish how one entity can trust another one. The Quality of Service trust is an example of a trust metric that illustrates the belief of delivering a service with a certain standard by an entity in the future (Selis, 2017).

2. Trust propagation

To propagate trust in a trust management framework, centralised and decentralised methods can be used. In a centralised method, the central entity maintains and provides the trust relationship between entities. While in a decentralised method, trust information about other entities is created and maintained by each entity (Selis, 2017).

3. Trust aggregation

Trust aggregation in a trust management framework is created by combining trust information that is gathered in three ways. First, direct observation in which an entity creates trust by direct observation of another entity. Second, indirect observation, building trust without directly observing an entity. Third, through recommendations; when three entities can see each other, the trustor trust's the third entity, and will apply recommendations of the second entity's direct observations (Selis, 2017; Truong et al., 2017).

4. Trust update

Trust update is done by two methods: event-driven and time-driven. In the event-driven method, after a special event, the trust value is updated, while in the time-driven method, the changes of the trust value is based on time. In the time-driven method, the time and new information regarding the entity is more momentous than previous information (Selis, 2017).

5. Trust formation

Trust formation is the final phase of trust evaluation in a relationship. Single-trust and multi-trust are illustrated as two dimensions for trust formation. In the first dimension, only a single trust value is applied to build trust relationships, whereas in a multi-trust dimension multiple trust values are concurrently applied to build trust relationships (Selis, 2017).

In this regard, trust values may be applied in the following ways:

• One-by-one: every trust value is compared with a threshold value according to the application;
• Weighted sum: using weight factors according to each value's importance and then summing trust values;
• Scaled trust: scaling all trust values from highest to lowest importance (Selis, 2017).

For remote machines to build trust relationships, they must include security elements and abilities to create a trust boundary. These include methods (e.g., trust algorithms or reputation systems) for developing the trust boundary and transferring trust to an exterior entity (Hongsong et al., 2011).

This section summarised trust in the context of the actor's interaction. In the next sections we move to elaborate trust as a construct.

2.5.3.2.4 Dimensions of Trust

Trust literature, from different disciplines, identifies various dimensions of trust. Svensson (2001, p. 432) discovered trust as a multidimensional concept containing 22 dimensions like "confidence, predictability, ability, competence, expertness, intentions or motives, benevolence, motivation to lie, business sense and judgement, altruism, loyalty, integrity, congruence, consistency, fairness, character, openness of management, liking, respect, faith, acceptance, and security."

Most literature combines the above mentioned dimensions and introduces trust dimensions as competence (Bulińska-Stangrecka & Bagieńska, 2018; Oleszkiewicz & Lachowicz-Tabaczek, 2016), benevolence (Lee, Lee, & Suh, 2007; Selnes & Gonhaug, 2000), predictability, credibility (Chérif & Lemoine, 2019; Lassoued & Hobbs, 2015; Tandoc Jr, Yao, & Wu, 2020), honesty (i.e., integrity) (van Esterik-Plasmeijer & van Raaij, 2017) and/or reliability (Tayal & Bharathi. S, 2021).

2.5.3.2.5 Forms of Trust

Different perspectives and viewpoints have developed regarding trust over time. This evolution impacts the aim and nature of trust research. Organisational behaviour researchers argued trust is social relational vs calculative (Susarla, Holzhacker, & Krishnan, 2020). Social relational trust that arises from past interactions and social relationships. While calculative trust is based on the economic value of possible relationships and rational decision making regarding future conditions and assessing the benefits and costs (Poppo, Zhou, & Li, 2016; Susarla et al., 2020). However, Reich-Graefe (2014) challenges this viewpoint towards trust, and suggests that trust under the condition of uncertainty is the end of rational calculative decision making, as a trustee needs to take a decision based on limited information and bounded rationality (Reich-Graefe, 2014).

Another classification of trust includes swift trust, quick trust (Yusof, Zakaria, & Muton, 2017), fast trust (Blomqvist, 2002), or initial trust (Lu, Goh, & De Souza, 2018). Q. Lu et al. (2018, p. 71) define swift trust as "a form of trust occurring in temporary organisational structures, assumed by group members initially, and is later verified and adjusted." This form of trust is established when people need to do projects in a short time and they do not have time to develop trust based on trust proxies (Yusof et al., 2017). In online environments, Safari (2012) recognises another form of trust and calls it connected trust, which is formed fast due to relying on other people's experiences with the trustee. Blomqvist (2002) deduces swift trust is established in a highly dynamic, high-speed environment and/or under time limitation.

In the same way, Lewicki and Bunker (1996) introduce three forms of trust: 1) deterrence-based trust, 2) knowledge-based trust, and 3) identification-based trust. These three forms of trust are sequential and connected. Building trust at one level makes developing the next level of trust possible. First, deterrence-based trust is built on consistency of the behaviour based on what people will do. Next, deterrence-based trust develops knowledge-based trust which is based on predictability of someone's behaviour. It is created when one party has enough information about other parties to predict their future behaviour. Finally, knowledge-based trust moves to identification-based trust that occurs based on emotional connection and empathy with other parties' desires (Lewicki & Bunker, 1996).

2.5.3.2.6 Levels of Trust

Trust levels are created since trust is first formed and is changed by experience. The level of trust with another party in the relationship is affected by previous interactions with him/her/it (Rehman et al, 2017). Wang (2010) explained that in the customer-provider relationship, a customer's trust level also is influenced by the interaction's frequency between the provider and the customer (Wang, 2010). Trust levels are important, as little differences from former promises (e.g., delaying to meet a promised order) in higher levels of trust are ignored and so trust stays at its current level (Rehman et al, 2017). However, changes in trust levels are inevitable because crossing the threshold can alter this passive expectation of continuity into upper or lower levels of trust (Blois, 1999).

There are five proposed trust levels in literature (Rehman et al., 2017) as follows:
Zero trust: if two persons have not had any interactions, they will be at a zero trust level with each other. However, in the real world this would not exist. Since positive or negative trust always exists in diverse forms because of previous information, perception, or interaction. Even trust in other things causes a person to trust an unseen occasion. When a person starts to think about someone or something else, their perception about it expands and that affects a trustor's opinion towards future interactions.

Some trust: in this level, there is trust between the trustor and the trustee due to former interactions, formal or informal communication, information sharing, etc. This level of trust is the basis for the next interaction and transaction. As soon as a new interaction occurs, the new experience can ruin or improve this level (Rehman et al., 2017).

Blind faith: in this level of trust, the trustor is expanding on an enduring relationship with the trustee. Building this kind of trust is very hard, but to the same extent it is hard to break (Rehman et al., 2017). Mesly (2015, p. 23) defines blind trust as “an emotional state (different than mere cognitive myopia) by which a market agent willingly or unconsciously accepts to make himself completely vulnerable to the intentions or actions of another market agent, without any of the possible consequences, positive or negative, of this action by reducing the level of perceived prediction to or near zero.” In this level of trust, the trustor is aware of the presence of risk but accepts it completely without paying attention to its consequences.

Negative trust: this kind of trust is the result of unsatisfied former interactions between the trustor and trustee. It influences future probable interactions between parties.

Paranoia: the mistrust that is created by a previous betrayal in an interaction with the trustor. In this state, the trustor prevents having any interaction in the future with the trustee (Rehman et al., 2017).

Another representation of trust level focuses on trust generalisation. Blanket trust or complete trust is identified as a high level of trust in all aspects (Habibov, Auchynnikava, Luo, & Fan, 2019; Tuang & Stringer, 2008; Welch, 2006). Blois (1999) challenges this level of trust as he believes blanket trust rarely exists because of two reasons: Firstly, one person may trust another concerning certain behavioural aspects while this person could be distrusted in another aspect. Secondly, when parties do not have enough experience to judge each other they cannot assess each other’s trustworthiness.

2.5.3.2.7 Distrust

From a rational choice viewpoint, trust and distrust are distinct entities but connected, and this causes them to coexist in some situations (Chan & Yao, 2018; Guo et al., 2017; Kang & Park, 2017). They may exist concurrently in relational interactions and may have positive or negative effects in some social contexts (Kang & Park, 2017).

Distrust is not simply the lack of trust; it reflects pessimism, suspicion, and/or fear (Liu et al., 2017). Distrust in practice is illustrated as a mechanism which is not necessarily confined to interactions with unfamiliar actors (Kang & Park, 2017). Most of the definitions simply explain distrust as an absence of trust and consider trust and distrust as different ends of the same spectrum. If distrust is simply defined as the opposite of trust, the factors that affect building trust can decrease distrust. Created trust from repeated exchanges can decrease concerns about distrust. While there are factors regarding trust which balance or control other factors of distrust, it cannot be said distrust is the lack of trust and vice versa. Distrust can be described as doubt, suspicion or diffidence which causes a person to try finding other alternatives (Guo et al., 2017). It is also considered as a psychological disorder that needs addressing to prevent social contradictions and to increase collaboration (Kang & Park, 2017). Moreover, distrust is demonstrated as "a positive expectation of injurious action, captures individual's apprehension that their vulnerabilities will be exploited by an incompetent and irresponsible partner with ill intentions " (Liu et al., 2017, p. 623). In other words, distrust is a pessimistic view of the other's responsiveness and competence (Jones, 2019).

According to the literature there are two kinds of distrust: distrust as a behaviour and distrust as a belief. Distrust as a behaviour includes falsifying information, creating formal contracts or organisations, extending monitoring and controls, decreasing acknowledgment, declining collaborations or eschewing business transactions. Distrust as a belief is rooted in being aware of a person's abilities, intentions or actions and may be shown as an expectation of undesirable behaviour of a partner. It is also defined as a belief or expectation towards unacceptable acts of another party (Guo et al., 2017).

Antecedents of distrust can be classified into three categories:

1. The individual and behavioural characteristics of the distrustor. These factors affect the attitude of the distrustor to distrust.
2. The behavioural characteristics of the distrustee, and
3. The contextual factors that distrust forms in (Guo et al., 2017).

In a strategic relationship trust and distrust as substantial factors must act together since both of them are directly linked to strategic decision making (Guo et al., 2017; Kang & Park, 2017). Whereas distrust compared with trust has an expressive role in forming the behavioural intention of consumers, trust regulates a customer's commitment. While trust causes customers to accept vulnerability in online service interactions, distrust leads to negative emotions and fear of the provider of an online service. Consequently, distrust decreases the behavioural intentions of the customer to interact with the online service provider because of a pre-emptive desire to protect him/herself from the next malicious actions. Moreover, distrust forces customers to avoid untrustworthy online service providers because of their worries about economic and social matters (Liu et al., 2017).

Generally, individuals trust or distrust another party to fulfil a task only if another party has committed to do it (Hawley, 2014).

2.5.3.3 Commitment

Commitment is one of the important identified factors in marketing literature (Fruchter & Sigue, 2004; Mende & Bolton, 2011; Morgan & Hunt, 1994). It is a basic prerequisite of building relationships in marketing as it enhances productive and effective relational exchange (Morgan & Hunt, 1994). In the service context, commitment is a significant metric as it illustrates how customers understand service relationships (Mende & Bolton, 2011).

Morgan and Hunt (1994, p. 23) defined commitment as an “enduring desire to maintain a valued relationship” and in which the committed partner desires that the relationship endures and attempts to preserve it (Morgan & Hunt, 1994). Commitment is also described as the continuing desire to maintain a worthy relationship (Hsu et al., 2018; Tellefsen & Thomas, 2005). This desire shows the expectation of the party to gain benefits from continuing the relationship into the future (Johnson, 2007). Similarly, Standifer, Evans, and Dong (2010) defined commitment as an implicit or explicit pledge to the consistency of the relationship between the customer and frontline employees. Additionally, commitment can be defined as a desire of parties to expand a relationship and their tendency to make short-term sacrifices to preserve it (Martin, Gutierrez, & Camarero, 2004; Terawatanavong, Whitwell, & Widing, 2007). In some literature commitment is conceptualised as a “resistance to change” (Yanamandram & White, 2010, p. 570).

From a scholar’s viewpoint, commitment is the basis of a successful relationship that causes all parties in the relationship to reach positive outcomes (Morgan & Hunt, 1994; Standifer et al., 2010). It illustrates the importance of the customer-service provider relationship (Hsu et al., 2018).

In the customer-service provider relationship, customer commitment indicates that the customer is willing to maintain a valued relationship with the service provider (Hsu et al., 2018; Morgan & Hunt, 1994). Furthermore, it is the "customer's long-term orientation towards the business relationship" (Hsu et al., 2018, p. 166). When customers believe in their long-term relationship and bond with frontline employees they are more willing to engage in the relational exchange (Tellefsen & Thomas, 2005).

Commitment plays a fundamental role in relational exchange (Morgan & Hunt, 1994; Tellefsen & Thomas, 2005). It acts as a psychological bond that causes the seller and customer to stay together when they face a challenge (Tellefsen & Thomas, 2005). To enhance the desire of the customer to continue a relationship with a provider, especially when a service provider representative is a machine, commitment is a key factor for building long-lasting relationships (Hsu et al., 2018).

The bilateral nature of commitment is more significant in business service relationships. Business services include a broad range of activities when offering a service which intensifies the importance of frontline employees. Consequently, it adds to the probability of forming a strong bond between customers and frontline employees. First, due to the intangibility of services their value is based on the perception of the service provider's performance. Next, customer needs are usually complicated and unique. Frontline service employees often are more knowledgable regarding these needs and they apply this knowledge to meet customer needs in a customised way. Following on from this, because of the importance of frontline employees (e.g., creativity and skills) to provide and deliver services diversely, frontline employees play a pivotal role in the relationship among customers and service organisations. So it is expected that customers form bonds with frontline employees (Tellefsen & Thomas, 2005).

Researchers consider, there to be two dimensions for commitment:

- A behavioural dimension
- A temporal dimension (Liu, Su, Li, & Liu, 2010; Martin et al., 2004)

2.5.3.3.1 Behavioural

Behavioural commitment is related to current behaviours, sacrifices, and promises. It generally illustrates "the emission of signals, to the investment and concern and help for the other partner" (Martin et al., 2004, p. 56). Marketing literature categorises the organisation's behavioural commitment to partners as calculative (i.e, instrumental) and affective (i.e., loyalty) commitment. Calculative commitment refers to the benefits of maintaining and the costs of leaving the relationship, while affective commitment refers to a sense of fidelity and faithfulness (Liu et al., 2010; Martin et al., 2004).

Calculative commitment is based upon objective causes, cancellation or switching costs (Youssef, Johnston, AbdelHamid, Dakrory, & Seddick, 2018). It is a special component or motivation of commitment which is explained as the extent to which the customer feels the need to preserve the relationship (Yanamandram & White, 2010).

Calculative commitment is also explained as a cognitive assessment of the instrumental value of continuing relationships with an organisation, frontline employees or a brand. Consequently, it includes calculating the benefits of continuing a relationship and the costs of leaving it (Morgan & Hunt, 1994; Yanamandram & White, 2010). In other words, calculatively committed customers continue a relationship when the costs of leaving the relationship surpass its expected benefits (Yanamandram & White, 2010).

Calculative commitment explains the state of dependence experienced cognitively as an evaluation of the benefits that would be lost if the relationship is left. It is a type of structural bonding that connects the relationship's parties due to mutual benefits, and it shows a bit negative motivation to continue the relationship (Liu et al., 2010). Generally, calculative commitment is an economic concept of commitment which results from how customers find an organisation or its services beneficial (Johnson, 2007). Consequently, customers can calculatively be committed to machines as frontline employees in order to receive the service.

In comparison, affective (i.e., loyalty) commitment refers to desires and feelings (Martin et al., 2004), and it is illustrated as the state of dependency experienced as a feeling of fidelity or faithfulness (Liu et al., 2010). Affective commitment shows the party's affection and eventuates from a strong sense of emotional loyalty and dependence on the relationship. This kind of commitment demonstrates that the connection relies on social and emotional feelings instead of economic subjects and motivation (Liu et al., 2010; Martin et al., 2004). Also it can be said that affective commitment refers to maintaining a relationship that relies on feelings of loyalty and affiliation (Youssef et al., 2018). Previous literature does not recognise this form of commitment in human-machine relationships. However, when considering humanlike machines, forming affective (i.e., loyalty) commitment in human-machine relationships may be possible.

2.5.3.3.2 Temporal

The temporal commitment demonstrates intentions for future commitment. It refers to the tendency to continue a stable relationship through time (Kim & Frazier, 1997; Martin et al., 2004). Temporal commitment or continuance commitment illustrates a customer's desire and intention of continuing a relationship with the other party (Kim & Frazier, 1997; Yau & Tang, 2018). It also refers to the longevity of the customer-service provider relationship (Yau & Tang, 2018).

Presence of conflict (i.e., disagreement) in the customer-service provider relationship prevents parties having confidence in each other’s temporal commitment (Kim & Frazier, 1997); while satisfaction has a positive effect on building temporal commitment (Yau & Tang, 2018). Moreover, Yau and Tang (2018) argued that in technology-based service encounters, affective and calculative commitment have a significant effect on enhancing temporal commitment.

2.5.3.4 Rapport

Rapport has been investigated in various disciplines regarding human interactions (Macintosh, 2009). Rapport is an important relational variable in the service context since it contributes to positive relational outcomes (e.g., loyalty, positive WOM) (Macintosh, 2009) and affecting perceived service quality (Qiu et al., 2020). Hence rapport can build a favourable psychological atmosphere and improve the customer service experience (Qiu et al., 2020). In addition, forming rapport in the service provider-customer relationship leads to increasing trust, as rapport causes uncertainty to decrease between two parties (Gremler & Gwinner, 2000; Gremler, Gwinner, & Brown, 2001). Rapport also has a significant influence on service recovery through establishing and maintaining relationships in service encounters (Macintosh, 2009).

Gremler and Gwinner (2000) defined rapport as “a customer’s perception of having an enjoyable interaction with the service provider employee, characterised by a personal connection between the two interactants. They conceptualised and introduced personal connection and enjoyable interactions as rapport dimensions (Gremler & Gwinner, 2000, p. 92).” The personal connection dimension is about the deep feeling of affiliation and bond between related parties. An enjoyable interaction is an affective evaluation of two parties' actual interactions (Macintosh, 2009).

Qiu et al. (2020) use ‘warm service’ expression to talk about rapport. They argued that the perception of warm services is conventionally about rapport building between customers and frontline employees (Qiu et al., 2020). Huang and Rust (2018) believed that in order for the robotic service encounters to prepare a warm service for customers, humans and robots need to work together, as service robots have not been outfitted properly with social elements. However, research shows that if customers perceive the social presence of service robots, they can form a rapport with them but it is different from the rapport between humans (Qiu et al., 2020; Van Doorn et al., 2017), since rapport forms between customers and robots due to quasi-social relationships (Qiu et al., 2020). Moreover, a service robot’s characteristics could give rise to a customer’s perception of rapport. Customers are more willing to form rapport with service robots when they perceive them as more humanlike and intelligent rather than machinelike. It is proposed that for service firms to build customer-robot rapport they need to improve robot design regarding anthropomorphic features especially in terms of robot intelligence (Qiu et al., 2020).

Consequently, regarding the significance of interpersonal relationships in service encounters (i.e., interactions between frontline employees and customers in service delivery) rapport needs to be investigated in AI-based service encounters.

The previous sections have explained different stages of the customer journey that build the overall customer experience across the entire customer journey. A customer journey is an engaging story of a customer’s interaction with a service that helps organisations to have a better understanding of the customer experience (Følstad, Nordheim, & Bjørkli, 2018). Understanding customer experience and customer journey is vital for organisations as customer experience is a strategic marketing investment (Kranzbühler, Kleijnen, Morgan, & Teerling, 2018; Lemon & Verhoef, 2016). For this reason, it is necessary to examine the customer experience. Due to the adoption of a systemic view towards customer service experience by this research, the following section summarises and draws conclusions on the previous sections (i.e., customer journey stages) of the customer service experience and explains these in more depth.

2.5.4 Customer Experience

In traditional literature, the customer experience was illustrated as the perceived outcome of the customer's interactions with the organisation throughout the service process (Kranzbühler et al., 2018). However, its concept has been changed to a contextual and systemic view (Trischler, Zehrer, & Westman, 2018). This research tries to investigate it from a network and ecosystem viewpoint.

Customer experience is a broad concept that can be described as an umbrella construct that embraces and includes a different set of incidents and occasions (Kranzbühler et al., 2018). It can be defined as a customer journey that is built by an iterative and dynamic process through time and includes multiple touchpoints (Trischler et al., 2018). In respect to service literature, service experiences are the result of interactions between customer and organisations, related systems, service processes, and frontline employees in the service context, which stimulate reactions (McColl-Kennedy, Zaki, Lemon, Urmetzer, & Neely, 2019; Sorooshian, Salimi, Salehi, Nia, & Asfaranjan, 2013). Customer experience also refers to a psychological feeling that is explained as the subjective response or perception of service delivery (Zhang et al., 2017). Indeed, the customer experience is general and includes a customer's affective feelings and physical responses (Sorooshian et al., 2013), whereas from a holistic perspective, it encompasses multiple touchpoints in a customer journey including cognitive, affective, emotional, social, and sensory factors (McColl-Kennedy et al., 2019).

That is to say, the customer experience is a multidimensional construct that concentrates on cognitive, emotional, behavioural, sensorial, and social responses of customers to the organisation's offering across the customer's purchase journey through multiple touch points (Batra, 2018; Keiningham et al., 2017). Customer experience denotes direct or indirect interactions of the customer with a series of actors in the market (Keiningham et al., 2017; Teixeira et al., 2012). Generally, customer experience is co-created via interacting with the various service elements (Teixeira et al., 2012).

The main elements of the customer experience consist of value creation elements (e.g., resource, context, activity, interaction, and customer role), direct emotions and cognitive response from the customer to touchpoints (McColl-Kennedy et al., 2019). Emotional experiences are pertaining to service encounters. Emotional experiences are connected to intellectual knowledge and consequently affect customer behaviour (Rambocas, M. Kirpalani, & Simms, 2014).

On the one hand, scholars have traditionally divided customer experience research into static and dynamic groups from organisation and customer perspectives. The organisational perspective deals with the creation of customer experience while customer perspective is concerned about the customer experience perception (Kranzbühler et al., 2018).

The static customer experience perspective is explained how customers experience touchpoints at a specific time. In view of this, a static customer experience is a cognitive, affective and sensory assessment of touchpoints with an organisation by a person at a specific point in time. In contrast, a dynamic customer experience shows how customer experiences develop over time. The dynamic customer experience is a cognitive, affective and sensory assessment of a set of direct or indirect touchpoints with an organisation during the entire customer journey. It is generally set up by a series of static customer experiences of touchpoints with an organisation (Kranzbühler et al., 2018).

Organisational perspective research concentrates on building customer experiences that are mostly static, while customer perspective research refers to customer perceptions of those experiences (Kranzbühler et al., 2018). Static customer experience research concentrates on subjects that are not controllable by the organisation (e.g., environment and individual) and how these subjects influence customer experience. From the dynamic approach, research investigates how satisfaction changes across the customer journey, and how perceptions of negative moments influence the customer experience over time. In this approach, customers evaluate their journey cognitively and affectively with their senses (Kranzbühler et al., 2018). According to this classification, this research focuses on the dynamic customer perspective.

On the other hand, customer experience research has differentiated between conceptualising offline and online experiences. They propose the offline experience dimension as: cognitive, affective, sensory, social, and physical. Parallel with four basic systems, cognition, affect, relationships, and sensations' online experience is conceptualised as comprising of four dimensions: informativeness (cognitive), entertainment (affective), social presence (social), and sensory appeal (sensory) (Bleier, Harmeling, & Palmatier, 2019).

- *Informativeness* is explained as the extent to which an online platform provides customers useful and resourceful information. It is the primary cognitive dimension that the online customer experiences. Informativeness encompasses the functional aspect and value of experience for the customer and usually is goal-oriented, objective and impersonal.

- *Entertainment* is defined as an instant pleasure that is gained by the experience without its effects on facilitating shopping tasks. In online shopping, entertainment is fun and enjoyment that is a result of shopping.

- *Social presence* illustrates the sociability, warmth, and feeling of contact with another person that the online platform provides. It leads to enhancing perceived tangibility and psychological aspects of service (e.g., closeness). Social presence also raises “pleasure, arousal and flow" in online shopping and increases intentions to purchase and loyalty (Bleier et al., 2019, p. 101).

- *Sensory* shows sensory elements of the customer experience. It refers to the stimulate sight, smell, sound, taste, or touch. In an online environment, it illustrates the way that platforms stimulate the senses. Evaluating the sensory level is done automatically and influences customer preferences (Bleier et al., 2019).

When characterising current experiences, scholars underline the importance of past or similar experiences (Kranzbühler et al., 2018). Previous experiences are the basis of expectations regarding the future interactions (McColl-Kennedy et al., 2019). Interactional experiences are vital for service industries as they account for changing customer behaviour and retaining the customers. According to previous literature, interactional service experiences represent the way in which the customer and frontline employee face each other (Albrecht et al., 2016). However, it can be completely different, by the intervention of emergent technologies such as artificial intelligence. In addition, the customer experience (i.e., interactive experience) is considered as an antecedent of customer engagement (Mohd-Ramly & Omar, 2017) in demonstrating the integration of relationship marketing with customer engagement (Vivek et al., 2012).

2.5.4.1 Customer Experience: The Antecedent of Customer Engagement

Customer experience is considered as a resource to engage customers with a service/product physically, mentally, socially, and emotionally that boosts customer-organisation interactions (Mohd-Ramly & Omar, 2017). From the consumer value perspective, the motivation of customers to engage depends on the expected value from the experience (Vivek et al., 2012). Customers gain experience, whether positive or negative, when they purchase, that builds a degree of satisfaction and feelings about the company (Moliner-Tena et al., 2019).

Organisations concentrate on the relationship quality with their customers and also maximising outputs beyond customer purchases. The relationship quality between customer and organisation is related to level of satisfaction resulting from the relationship and the level of a customer's emotional connectedness to this relationship (Pansari & Kumar, 2017). Customer satisfaction is based on anticipated expectations and the prediction of an experience that will occur in the future. In a similar way, the customer experience is based on the degree to which the anticipated benefits (e.g., utilitarian, hedonic, and social) are acquired. Satisfaction results from the combination of customer experience dimensions which are unique for every customer and leads towards customer engagement (Moliner-Tena et al., 2019). Satisfaction and emotion are antecedents of engagement as it emerges after shaping the relationship informed by trust and commitment (Pansari & Kumar, 2017). As a consequence, customer engagement is an emotional bond with an organisation, brand or service derived from the collection of service experiences that contains a proactive and desirable psychological state (Moliner-Tena et al., 2019). In other words, a relationship develops to the engagement stage when it is satisfying and has emotional bonding (Pansari & Kumar, 2017).

Moliner-Tena et al. (2019) proposed a framework to study the relationship between customer experience and customer engagement, in which satisfaction and emotion were considered as customer engagement antecedents. Their results confirmed that the customer experience of the service received in banking has a significant relationship with customer engagement with their bank. Zhang et al. (2017) in their research also showed that customer experience raises community engagement, and in turn, increases word-of-mouth intention. On the one hand, previous research confirmed customer experience as an antecedent of customer engagement (Bowden, 2009; Mohd-Ramly & Omar, 2017). On the other hand, customer engagement and interacting with a service provider creates their experience of the shopping journey (Følstad et al., 2018). Generally, customer experience is the aggregation of the customer's experiences at any touchpoint of the customer-service provider relationship (Joshi, 2014). Frontline employees are the first touchpoint between the customer and service provider, that by increasing the AI-based organisational frontline (e.g., chatbots and virtual intelligent assistants) they become more virtual. Given the importance of emotion in customer relationships as an outcome of customer experience, especially in the service context, there is a gap in the literature in regards to emotional aspects of the customer service experience of AI-based service encounters. This gap needs to be addressed by considering intuitive AI and its resulting anthropomorphic features that make machines more human-like cognitively and behaviourally. This guides us to the main research question:

RQ: How does intuitive AI-based organisational frontlines affect the customer service experience?

2.6 Conclusion

This chapter summarises the body of literature that can help to understand customer experience and behaviour in intuitive AI-based organisational frontlines. This includes:

- Organisational frontline literature
- Literature on artificial intelligence with focus on anthropomorphism and machine behaviour
- Engagement literature
- Literature on use and gratification
- Literature on business-to-customer relationship
- Literature on customer experience

The literature on organisational frontlines define an organisational frontline and introduces interaction and interfaces as its dimensions. In this part of the literature, the importance of new ways of interaction (e.g., online) and related interfaces of those interactions was explained. Whilst previous research in this research area argued the utilitarian value for assessing the interfaces in the organisational frontline, while hedonic and social value also needs to be investigated.

The literature on artificial intelligence introduce the different levels of AI, and especially intuitive level AI, that is the focus of this research. Conversational agents as intuitive AI-based machines in the service context were examined and presented. Intuitive AI adds cognitive and behavioural features to conversational agents that causes users to anthropomorphise them (i.e., attributing human features to a nonhuman entity). However, former studies have investigated the physical anthropomorphic features, whereas cognitive and behavioural anthropomorphic features also need to be studied. In this section machine behaviour as one of the intelligent machine's characteristics was also explored. Moral machines and moral competence to justify machine behaviour was explained. Whilst literature in this area illustrated that machine behaviour has been investigated in other fields (i.e., computer science, robotic, engineering) to design moral and ethical machines, but this research investigates machine behaviour in the marketing context to have a better understanding of the customer-AI-based frontline employee relationship.

Literature on engagement emphasises the positive and negative antecedents of engagement from previous research (i.e., WOM, motivation, technological sophistication, reuse intention, privacy risk and uncertainty). Literature in this area underlines the need for further investigation on the effects of cognitive and behavioural anthropomorphic features that result from intuitive AI on engagement through these dimensions, which leads to the first research question:

(RQ1) How do intuitive AI-based organisational frontlines affect customer engagement in service encounters?

The literature on use and gratification summarised utilitarian, hedonic, and social gratification by focusing on an individual's different needs as a motivation for using new technologies. Literature identified that people use a technology as a medium to interact with other humans to obtain hedonic and social gratification. However, intuitive AI (e.g., machine learning, natural language processing) capable machines have bilateral conversations as one of the interaction parties and not merely as a medium which emphasises the necessity of research on this subject.

This body of knowledge also argued the effects of gratification on forming affinity and positive feelings towards media. This part of the literature led to the second research question:

(RQ2) How do intuitive AI-based organisational frontlines affect perceived gratification by customers in service encounters?

The next part of the literature in this chapter summarised business-to-customer relationship studies that have focused on social and emotional relationships based on the social exchange theory and relationship marketing. This body of knowledge acknowledges the importance of face-to-face interactions in creating emotion and social value in customer relationships, which can lead to forming trust, affective commitment, and rapport in human employee-customer relationships. The importance of relationship marketing and the omnipresence of intelligent machines as frontline employees for service delivery, highlights the need for investigating the effects of cognitive and behavioural anthropomorphic features of intuitive AI-based organisational frontlines on forming and developing human-machine relationships. This part of the literature resulted in the third research question:

(RQ3) How do intuitive AI-based organisational frontlines affect human-machine relationships in service encounters?

The last part of the literature looked at the customer experience, and focused on different types of customer experiences (e.g., online and offline) and their pros and cons. By comparing man vs. machine or algorithms vs. emotions we come across challenges in regard to evaluating the effects of artificial intuitive intelligence on customer experiences from an organisational frontline viewpoint, which illustrates the requirement of further research on this topic and leads to the main research question:

(RQ) *How do intuitive AI-based organisational frontlines affect the customer service experience?*

Based on the above reviewed literature, this research finds that the human-intelligent machine relationship may be different from what we understand so far from the literature on relationship marketing. Consequently, this research is going to address those research questions in the following chapters.

Chapter 3 Methodology

3.1 Introduction

This chapter outlines the adopted research philosophy and research methodology employed by the researcher in order to achieve the research aims. It is focusing on the research approach, research methods (e.g., data collection and data analysis techniques), validity and reliability of the research, and ethical considerations. In investigating the customer service experience of AI-based frontline employees and in giving consideration to the philosophical assumptions of the researcher, this research is positioned within the interpretivism paradigm. The research's qualitative inductive approach, as well as techniques of data collection (i.e., semi-structured interviews and documents) and methods of data analysis, had been informed by the interpretivism paradigm. In the following aforementioned research the methodology area will be explained in detail.

3.2 Research Philosophy

Research philosophy is the basis of every research and denotes beliefs and assumptions to develop knowledge. It involves the realities researchers confront in their research (ontology) or about human knowledge about realities (epistemology) (Saunders, 2019). The way researchers think about the nature of reality and what will be considered as facts concerning this reality defines the nature of research questions and determines all methodological choices.

When considering the nature of reality researchers take different positions. The realism position believes that the world is tangible and external and knowledge can progress only by observation. Internal realism presumes there is a single reality and that achieving reality directly is impossible. The position of relativism proposes scientific laws are created by people and are not simply out there to be discovered. While the position of nominalism suggests that there is no truth and social reality is the establishment of people by language and discourse (Easterby-Smith, Jaspersen, Thorpe, & Valizade, 2021).

Ontology	Realism	Internal Realism	Relativism	Nominalism
Truth	Single truth	Truth exists but not discovered	There are many truths	There is no truth
Facts	Facts exist and can be uncovered	Facts are tangible but cannot be gained directly	Facts depend on the observer's viewpoint	Facts are all human establishment

Table 3.1 Different Ontologies

Relevant to the nature of reality, there are epistemological questions (e.g., How this reality can be understood? What could be taken as a true display of reality?) which can be answered from different positions. Depending on the nature of knowledge some researchers argue that 'true' knowledge about reality must be objective and transmitted in tangible form. It should be independent of the researcher and social actors. As a result, reality can be obtained from the world (objectivism). Researchers with this viewpoint are looking for casualty and relationship between objective factors. These relationships are tested and unsupported hypotheses are discarded (Burrell, 1985).

At the other end of this continuum are those researchers who believe knowledge about reality is based on interpretation, sensemaking, and people's experiences (subjectivism). They presume knowledge is spiritual, predicated by experience and insight of a personal nature. Thus to understand reality it is required to investigate how social actors experience the reality in specific situations. Researchers with the subjectivism viewpoint are not looking for universal truth and they believe that research may enable access to the meanings which are attributed by people to their experience and social worlds (Burrell, 1985; Saunders, 2019). Detected meanings embedded in context and practices establish scientific knowledge regarding reality. Researchers also play a significant role in data analysis, interpretation, and helping as an instrument of gaining knowledge regarding reality (Saunders, 2019).

The ontological and epistemological viewpoints of the researcher (i.e., philosophical view) affect the types of research questions and the approaches to answering these questions. Various combinations of research ontology, epistemology, and the Methodology (i.e., the characteristics and methods of collecting data and analysis) form a set of paradigms for researchers (Burrell, 1985; Guba & Lincoln, 1994; Saunders, 2019).

3.3 Research Paradigm

The main paradigms which guide social science research and are prevailing in business studies are categorised as positivism, realism, pragmatism, and interpretivism. In the following sections, all paradigms will be presented before the paradigm for this research is outlined.

3.3.1 Positivist

Positivism is one of the oldest and dominantly used paradigms (Cavana, Delahaye, & Sekaran, 2001; Neuman, 2011). Positivists' ontological assumption is realism and the epistemology of positivism highlights the researcher and the researched are separate and independent of each other (Easterby-Smith et al., 2021). Easterby-Smith et al. (2021, p. 51) noted "The key idea of positivism is that the social world exists externally and that its properties can be measured through objective methods, rather than being inferred subjectively through sensation, reflection or intuition." Positivist research applies objective measures and it is related mostly to quantitative data (but can use qualitative) (Cavana et al., 2001). Positivism mostly uses experimental methodology and includes methods with testing hypotheses through surveys and statistics (Neuman, 2011).

3.3.2 Realism

A Realist considers what we sense is reality and reality is independent of the observer's mind. Realism has an objective viewpoint. In social science, two forms of realism are constructed to have a better understanding of realism: Direct Realism and Critical Realism.

Direct realism concerns philosophy and explains that what humans experience with their senses, represents the world exactly. However, critical realism argues a human's experiences are their sensations and the image of objects in the real world (Saunders, 2019).

3.3.3 Pragmatism

Pragmatism happens because of actions, situations, and consequences rather than former conditions. Pragmatism believes truth drives at the time and it is not duality between a reality dependent or independent of the human mind. Pragmatists focus on the research problem and apply all approaches for understanding the problem as opposed to concentrating on methods (Creswell & Creswell, 2017). Pragmatists believe research questions are determinant of research philosophy (i.e., ontology, epistemology). When the research question does not show clearly which philosophy must be used the researcher can adopt a pragmatism approach and apply a different research philosophy. Pragmatists believe that there is not any single viewpoint that provides a complete picture of reality. They argue there are many ways to interpret the world and to carry out research (Saunders, 2019). It is applied mostly for mixed methods research (Creswell & Creswell, 2017).

3.3.4 Interpretivism

Interpretivism refers to reality as socially constructed, and humans in their daily interactions with each other give meaning to them. It has also been mentioned as constructivism in the literature. Interpretivists believe reality is not objective nor an external existence (Easterby-Smith et al., 2021). The essence of interpretivism in many aspects of social reality are specified by people instead of objects and external elements. Consequently, it is required to understand structures and meanings that people form based on their experiences. Interpretivists try to understand people's various experiences rather than investigating external factors to understand behaviour (Easterby-Smith et al., 2021). The interpretivist researchers are drawn to investigate human's lived experiences and engage with human subjects. It allows the researcher to discover socially constructed meaning in the way perceived by the person or the group of people (Cavana et al., 2001). Interpretivism emphasises what people individually or as a group are thinking and feeling, and considers the ways in which people communicate together (e.g., verbal or non-verbal) (Cavana et al., 2001; Easterby-Smith et al., 2021).

Interpretivism argues humans experience physical and social reality differently. It explains the world is dominantly what people imagine it to be and reality is socially constructed (Cavana et al., 2001). They criticise positivists by arguing that deep insights into the complex social world of business and management will be lost if this complexity is only summarised to law-like generalisations. Interpretivism focuses on carrying out research between people rather than considering them as objects. Interpretivist researchers need to enter the research subject's social world and *interpret* and comprehend their world in the way they see it (Saunders, 2019). Saunders (2019) mentioned that interpretivism could be appropriate for business and management research (e.g., marketing, organisational behaviour). The interpretivism paradigm is applied mostly for in-depth investigations and qualitative method research (Saunders, 2019).

For the purpose of this research, an interpretivism paradigm was adopted. It comes from relativist ontology and subjectivist epistemology. These philosophical assumptions drive the methodological approach, methods for data collection, and data analysis. This research adopted interpretivism to understand the personal meaning of participants using AI-based frontline employees. It aims to investigate how participants experience the service offered by AI-based frontline employees and make sense of this, and how these meanings construct participant's perceptions of a service experience. This research following the interpretive approach looked at individual sensemaking and experience with respect to intuitive AI to identify patterns that might help explain the nature of the phenomenon of interest (i.e., customer service experience of the intelligent machine).

Moreover, this study tries to understand participant's meanings of experiencing offered services by AI-based frontline employees that are viewed as being related to the context (e.g., participant's characteristics and conditions). To summarise, this research applied the interpretivism paradigm to understand in a meaningful way the subjective reality of a customer's behaviour to understand their motives, actions, and intentions towards AI-based frontline employees and their offered services.

3.4 Methodology and Approach to The Research

The nature of interpretivism calls for research methods that facilitate extracting an in-depth insight into what people do and the way they think. Interpretivist research must have an exploratory orientation to understand people's perspectives and reveal how people's perspectives justify their actions. Well suited research methods to the interpretivist paradigm are methods based on qualitative approaches and qualitative data analysis that are gained through observations, conversations, and/or text analysis (Easterby-Smith et al., 2021; Neuman, 2011; Saunders, 2019).

Qualitative research focuses on the process (i.e., what is observed and analysed to find how some events influence others) rather than the relationship between variables. Qualitative research results in rich non-numerical data that needs to be interpreted and understood by the researcher as opposed to statistical analysis. Rich and deep qualitative data leads to having a better understanding of a participant's views and perspectives and realising how they make sense of reality (Flick, 2018b; Silverman, 2006). This is especially important in customer behaviour researches. This research focuses on how AI-based frontline employees influence customer's perceptions of gratifications. To answer this question, a detailed account of a customer's experience is required, which cannot be achieved with quantitative methods.

Another logic to support applying a qualitative approach for this research can be explained by the research objective of exploring phenomenon about which little is known so far (i.e., intuitive AI: machines with human characteristics that can learn) (Saunders, 2019).

3.5 Research Approach

Researchers, apart from their research interest and their experience about the research subject, add some theoretical perspective to the research that guides it from the start (deductive approach). Or they are developed more at the end of the study by giving meaning to the findings (inductive approach). By taking the deductive research approach, theory heads the research and suggests what the researcher must look for. This kind of research usually starts with formulating hypotheses based on the theory that guides data analysis. The deductive approach moves from theory to data to find causal relationships between variables by collecting quantitative data (Cavana et al., 2001).

The inductive approach moves in the reverse direction from data to theory. The main objective of inductive research is analysing data to find patterns and themes to formulate relationships and develop theory (Cavana et al., 2001). Qualitative research usually starts with the inductive approach to develop a deeper theoretical perspective. However, it could also start with the deductive approach to test an existing theoretical perspective. This research initially took the inductive approach, that corresponds to the research objectives of identifying and understanding customer behaviour and their experiences of interacting with AI-based FLEs that display human characteristics. In progressing the research, it moved towards the abductive approach to analyse research data through systematic combining. Systematic combining was done by the matching of empirical results and theory by moving between theoretical frameworks and data analysis which resulted in direction and redirection of the research process (Dubois & Gadde, 2017; Dubois & Gadde, 2002). Research was started by reviewing the service marketing literature. Then research data was collected and coded. After the first-round of coding the anthropomorphism code emerged which meant then returning to the theoretical framework. Next, back to analysing data for a second round of coding. In this stage the gratification code emerged. After that the researcher went back to the theoretical framework to study related frameworks to gratification.

3.6 Research Methods

Research methods are specific techniques with a course of action applied for collecting data and data analysis (Chapman, 2005). This research had chosen the research methods compatible with the interpretive paradigm and qualitative inductive research approach. Saunders (2019) outlined research methodological choices (Figure 3.1). He explained the main choice from applying one data collection technique (i.e., mono method) to applying more than one data collection technique (i.e., multiple methods). Applying multiple methods can prevail over mono method's weaknesses and preparing the scope of a better approach to data collection, analysis, and interpretation. In a multiple method approach, the researcher can select more than one data collection technique within either a quantitative or qualitative design (i.e., multimethod quantitative study, multimethod qualitative study, and Mixed method research) (Saunders, 2019). This research chose a multimethod qualitative approach.

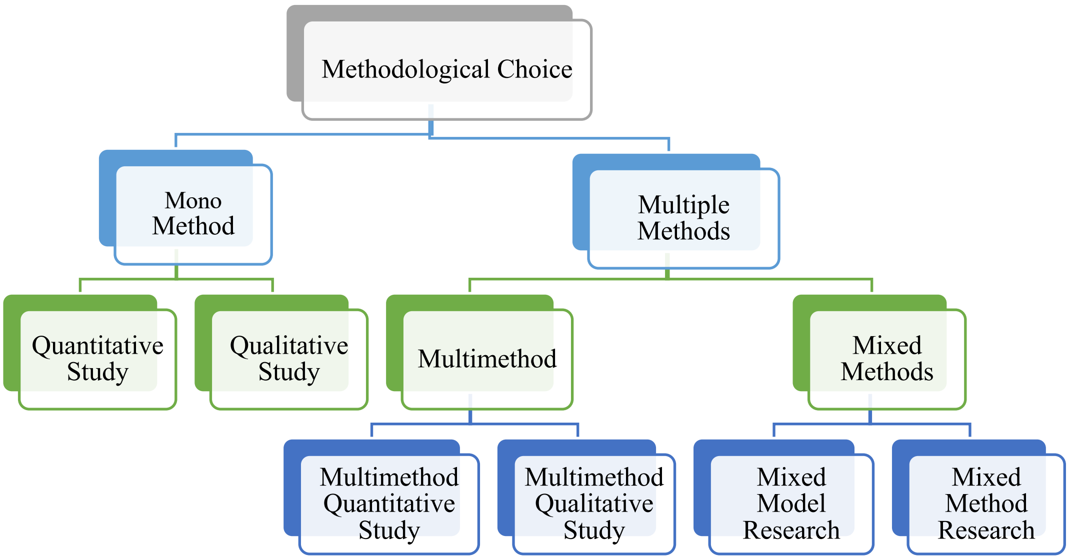

Figure 3-1: Methodological Choice (Saunders, 2019, p. 165)

3.7 Data Collection Methods

Qualitative research applies diverse methods for data collection (e.g., interview, observation, and secondary documents) (Creswell & Creswell, 2017; Easterby-Smith et al., 2021). For this research natural language data was collected from individuals (i.e., primary and secondary data) through interviews and documents. The interview method was selected as the primary method to collect data. This allowed for collecting empirical data via conversations with people about their experiences. The researcher used interviews to understand the participant's perceptions of interacting with AI-based frontline employees and their effects on experiencing services offered by them. Additionally the researcher chose the documents (people's comments on YouTube videos about selected AI-based frontline employees for this research) data collection method as a second source of data for triangulation (e.g, rather than only one data source). Moreover, it enabled the researcher to witness real language and words of people (e.g, interviewees may feel uncomfortable and be reluctant to talk about their emotional feelings towards a machine (it is not normal)). Consequently, with two data sources, it is possible to more accurately reflect the customer experience of AI-based frontline employees and acquire more consistency.

3.7.1 Primary Data: Semi-Structured In-Depth Interview

Interviews are divided into three types. Structured interviews which are characterised by highly formalised and structured questions (i.e., the researcher develops research questions before the interview and does not change them during the interview). Structured interviews are conducted from the deductive approach to collect quantifiable data (Cavana et al., 2001; Saunders, 2019).

Unstructured interviews are completely informal and are used to explore a research area in depth. The researcher does not have any predetermined question to ask; instead gives the opportunity to the participant to talk about events, behaviour, and beliefs related to the research area. The interview will be conducted through the interviewee's perceptions (Saunders, 2019).

Semi-structured interviews are often applied for qualitative research. In semi-structured interviews, few questions (if any) based on the subjective theory are developed in advance. Questions asked to vary from interview to interview based on the flow of the conversation. The researcher uses an interview guide in relation to key topics that are to be discussed and questions to be asked. The researcher stays open to a participant's answers to each question.

New questions will be asked if research topic areas are not covered by the initial question. Semi-structured interviews constitute benefit features of structured and unstructured interview techniques (Flick, 2018b; Saunders, 2019). Researchers need to conduct in-depth interviews when research questions cannot be answered briefly, and they need more explanation about an interviewee's answers (e.g., when there is a need to ask participants to give an example or explain their experience) (Rubin, 2005). Through probing and prompting, an in-depth interview allows the researcher to uncover the participant's view, feelings, and experience.

This research mostly relied on primary data from applying semi-structured in-depth interviews. It was guided by the literature and theoretical perspective, and simultaneously it allowed the researcher to ask additional questions if new areas appeared or the participant's answers needed more clarification.

3.7.2 Interview Preparation and Protocols

The interview questions were primarily set regarding research questions, literature, and the adopted theoretical framework of the research. To improve the quality and reliability of the research in the preparation phase, a protocol (Appendix 1) was developed for investigation and for when a pilot study was conducted (Easterby-Smith et al., 2021). The protocol helps the researcher to focus on the topic and questions, to recognise required resources to answer the questions, and to predict obstacles even before conducting the research. Two pilot interviews were conducted using the guideline to refine the interview protocol. Consequently, several questions were added based on the new themes that emerged from pilot interviews. Saunders (2019) noted that pilot interviews act as a strategy for refining interview protocol. In the final stage of the data collection, one follow-up interview is conducted that comprises further developed questions.

Based on the research plan, an information sheet and a consent form approved by the ethics team of the University of Otago (Appendix 2) as standard documents were shared with all participants before they participated in the research.

In the case of this research, the overarching research questions were reformulated into a series of eight generalised interview questions (see Appendix 1, interview protocol), that were probing in nature. Before starting the interview questions, the researcher asked the interviewee to introduce him/herself and asked about the model of the interviewee's intelligent assistant, in order to tailor questions using the name of their intelligent assistants. The researcher usually started with "could you tell me about your intelligent assistants?" and continued with prompts and probes to ask related questions to their answers. Finally, at the end of interview, participants were given the opportunity to share any further points about their intelligent assistants.

Interviews were conducted on a one-on-one basis and internet mediated (Saunders, 2019). Interviews were conducted via Zoom software (i.e., all interviews are recorded and transcribed using Zoom application (see section 3.8)) through teleconferencing. The positive points of internet mediated interviews are that they cover the convenience of both parties and geographical area (Cavana et al., 2001). As the data collection phase was conducted during the Covid-19 pandemic and associated social and travel restrictions (April and May 2020), interviewing by Zoom enabled the researcher to have access to participants around the world while preserving face-to-face interview feature benefits that otherwise would not have been possible under the circumstances.

3.7.2.1 Sampling

Sampling in qualitative research can refer to a range of factors such as " selecting people, groups, sites and situations for collecting data or to build corpus to set up data for an analysis" (Flick, 2018a, p. 32). In qualitative research, sampling does not merely refer to sample cases, individuals, and materials, but also refers to sampling inside materials, documents, and cases (Flick, 2018a).

The main criteria of sampling that links both data sets used in this research (i.e., interview and YouTube comments) are the three types of intelligent assistants: Siri, Alexa, and Google assistants. For the interviews, it is having experience of using these intelligent assistants. For the secondary source of data, it is commenters' opinions about the contents of videos about these particular intelligent assistants.

3.7.2.1.1 Primary Data (interviews)

In qualitative research, a non-probability sample is better suited to the purpose of this research (Cavana et al., 2001; Neuman, 2011). In non-probability samples, the researcher does not need to determine sample size beforehand and has limited knowledge about the population that the sample is taken from (Neuman, 2011). There are different ranges of non-probability sampling techniques: Quota, Purposive, Volunteer, Sequential, Haphazard (Neuman, 2011; Saunders, 2019). At one end of this range is quota sampling. Quota sampling is similar to probability sampling, as it aims to represent a total population. At the other end is haphazard sampling which focuses on getting a sample in any way that is fast and convenient. The other methods of purposive, volunteer and sequential sampling techniques position themselves within these boundaries (Saunders, 2019).

This research applied volunteer and sequential sampling techniques. In the volunteer sampling technique, participants volunteer to participate in research rather than being selected and includes snowball and self-selection techniques. Snowball sampling, which is also called network sampling, chain referral, reputational, and respondent-driven sampling, is a method for selecting the participants in a network (Neuman, 2011). In this method the researcher contacts the first cases in the population and then asks them to introduce further cases. They then go on to ask other cases to introduce more new cases and so on. The main problems of this method are identifying the first cases, and participants may introduce individuals similar to themselves (Neuman, 2011; Saunders, 2019).

Self-selection sampling is the second method of volunteer sampling. It gives permission to individuals to choose to take part in the research. In this method the researcher publicises their request for respondents through advertising within suitable media, or by inviting individuals to take part in research. Promotion can take place through different methods such as articles and advertising in magazines that the target group may read, postings on related internet newsgroups or discussion groups (Saunders, 2019).

In the sequential sampling method, researchers continue to select cases until they reach saturation point. This means a researcher gathers cases until he/she cannot find any new information or reaches a specific diversity of cases. This research advertised on intelligent assistant user group pages on Facebook like Google Home / Google Home Mini – Support (https://www.facebook.com/groups/128363527822120), which is a public group with 5.5k members, or Alexa Echo & Echo Show by Amazon (https://www.facebook.com/groups/954372741289650) which is a public group with 7.3k members. The researcher asked members if they would be willing to be interviewed about the research topic, with the option to contact the researcher by email (i.e., Self-selection sampling

(27 people)). Respondents were also asked to introduce other cases (i.e., snowball sampling (4 people)). The researcher continued sampling until saturation point was reached (i.e., sequential sampling). Coincidentally, most participants used two out of the three intelligent assistants (e.g., Siri and Alexa or Google Assistant and Alexa).

3.7.2.1.2 Secondary Data (Big Data)

Qualitative researchers can have access to a huge and diverse range of people and the content they create through social media. Collecting data from social media can be more scalable than traditional methods. The researcher is able scale data harvesting as soon as they are equipped with the resources to access and process data. This contrast with traditional methods (e.g., interviews and surveys) that need more resource from both researchers and participants. Social media data arises from real world social environments and encompasses a wide and diverse range of opinions without the necessity for researcher intervention or elicitation (Andreotta et al., 2019).

Due to the novelty of AI-based service research, it was deemed necessary to adopt a secondary source of data to triangulate the primary source of data. This study selected YouTube because most people can easily access it, and it allows users to post comments on videos, and these comments mostly represent opinions or queries about a video's content. YouTube allows the public at-large to communicate and collaborate in ways that disregard many traditional constraints (e.g., they can freely express their opinion and/or without the intervention of an interviewer). For the purpose of this research, the researcher wanted to identify if people have a forum to express their opinion towards their experiences of intelligent assistants freely and without intervention of interviewer, and whether these opinions reflect the ones from the primary data or not.

A collection of keywords was established to scrape the related posts. The keywords used were "Siri", "Alexa", "Echo Dot", "Amazon Echo", "Amazon Echo Show", "Amazon Echo Studio", "Amazon Echo Plus", "Amazon Eco Spot", "Amazon Echo Look", " Google Nest Hub", "Google Nest Mini", "Google Nest Audio", "Google Home", and "Google Assistant". This study used the DataMiner tool to scrape data (i.e., scraping data is the process of pooling data) from YouTube. The collected data were only the comments. Scraping data was done based on the year videos had been posted from 2020 to 2013 (i.e., newest videos to oldest) to reach the acceptable volume of data based on Kaisler, Armour, Espinosa, and Money (2013, p. 995) definition of big data "Big data refers to data volumes in the range of exabytes (10^{18}) and beyond (i.e., volume saturation)." This research also adopted a similar method to Lu, Webster, Peng, Chen, and Chen (2018) for data saturation. They analysed their data set day by day while they extracted more data every day. They stopped scraping data when they noticed patterns stayed stable and no new insights were added. In this research, the researcher stopped collecting data after analysing social data three times and seeing similar themes over three stages. Social data was analysed the first time with 10,000 comments (after reaching volume saturation), then the second time more data (around. 11,000 comments) were scraped and analysed, and finally the third , further comments (i.e., 12,941 comments) were scraped again and analysed. Collected data were stored in a CSV file to be processed.

3.7.2.1.3 Framing Big Data for Data Trustworthiness

This research applies an introduced framework by Andreotta et al. (2019, p. 1767) to frame data and increase social media data trustworthiness. By using this framework the researcher can overcome some of the social media data challenges (e.g., interactivity and volume) through automating some aspects of data collection and consolidation that result in a manageable volume of data to synthesize and interpret by the researcher (Andreotta et al., 2019).

1. Harvest social media data and compile a corpus
2. Use data science techniques to compress the corpus along a dimension of relevance
3. Extract a subset of data from the most relevant spaces of the corpus
4. Perform a qualitative analysis on this subset of data

In this research, the first stage of harvesting the social media data was done by the DataMiner tool (explained in sampling of the secondary source of data). The second and third stages were done through Leximancer. Leximancer, by applying a Bayesian learning algorithm, recognises concepts based on the frequency, interrelations, and co-occurrence of the concepts in each text corpus (Mahr et al., 2019). In this stage the researcher assesses the relevance of the words and combines some words (e.g., different names of all intelligent assistants (Siri, Alexa, Echo Dote, Echo Show etc., as OF). In the next stage Leximancer creates a visual map that shows how concepts are related to each other. Then in last stage the researcher interprets the visual map by considering themes, concepts, and their semantic relationships with other concepts (Figure3-2).

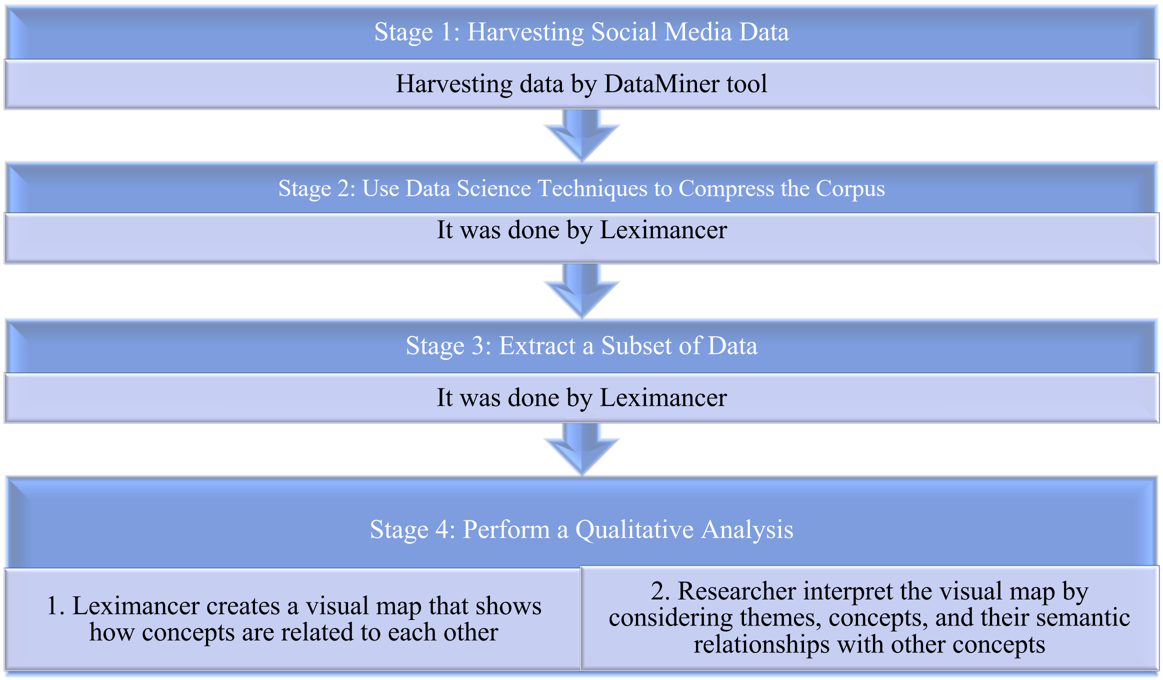

Figure 3-2: Social Data Framing

3.7.2.2 Participants and Interview Procedure

Users of Siri, Alexa, and Google Assistant were chosen as research samples because these intelligent assistants are more advanced in the world and companies use their technology in the role of frontline employees (e.g., Jamie (ANZ Bank intelligent assistant) but it is not advanced enough yet). They were released between 2011 to 2016 and have had enough time to become established in the market. Also, this research argues that behaviour of these intelligent assistants is transferable to service.

This research utilised volunteer and sequential sampling method (Neuman, 2011; Saunders, 2019). Participants were selected based on some criteria (e.g., participants aged 18 years and over, who have experience of using intelligent assistants for more than six months). After receiving the participant's interest to participate in the research, a consent form and information sheet were emailed to the interviewee. Following this, when participants signed and sent back the consent form to the researcher, an interview invitation (i.e., Zoom meeting invitation) was sent to participants according to their preferred date and time. The recruitment of participants was an ongoing process (i.e, it was not a pre-determined number) to reach the point where the amount of new information started to match previous information (i.e., since analysing data had been done simultaneously with data collection, the researcher reached the point where they couldn't get any further data on themes). In the sequential sampling method recruitment continues to gather participants until no new information emerges which is called saturation point (Neuman, 2011). In this research recruitment of participants from diverse countries and different ages (e.g., from 21 to 71)) allowed the researcher to consider several related factors to customer engagement and relationship. In total it took 31 interviews, plus one follow-up which was conducted after finishing the main phase of data collection, for the researcher to reach the saturation point. This research's interviews lasted 35–95 minutes with an average interview time of 50 minutes.

3.7.2.2.1 Participants Characteristics

This study conducted semi-structured in-depth interviews with 31 respondents, with the main purpose of exploring the customer service experience of intuitive AI-based organisational frontlines. Of the 31 respondents the average age was 40 years (Table 3.2).

Participant Number	Gender	Country	Intelligent assistant	Age	Education	Job
P1	Male	NZ	Siri	31	PhD student	Student(Turism)
P2	Male	NZ	Siri	29	PhD	Research fellow
P3	Female	AU	Google Home	41	MBA degree	Accountant
P4	Male	US	Siri& Alexa	36	Bachelor	Networking engineering
P5	Male	US	Alexa	25	PhD	Digital marketer and marketing director
P6	Female	NZ	Alexa	21	Master	Student (Master of chemical material engineering)
P7	Male	NZ	Google Home	32	Bachelor of music	Manager of marketing agency
P8	Male	US	Siri& Alexa	24	Bachelor	Teacher
P9	Female	NZ	Alexa	40	PhD	Postdoctoral
P10	Male	US	Google Home	70	MBA and an undergraduate degree in public administration.	Studio director
P11	Female	NZ	Alexa	25	Bachelor of Commerce	Client services administrator
P12	Male	NZ	Google Home	45	PhD	Postdoc
P13	Male	NZ	Google Home	23	Bachelor of Pharmacy	consultant in the healthcare industry

P14	Female	NZ	Alexa	55	Master	Senior policy officer at ministry of foreign affairs and trade
P15	Male	NZ	Alexa	21	Studying film and media and monitoring and Marketing sport development	Student
P16	Male	NZ	Alexa& Google Home	71	Post Graduate Diploma in Social Work	Retired- Army
P17	Male	India	Alexa	34	Master of Mechanical Engineering	Manager of production planning in Atlas Copco
P18	Male (visually impaired)	NZ	Google Home	49	Diploma	Collections consultant
P19	Female	NZ	Google Home	62	Diploma	Sales rep
P20	Male	NZ	Google Home	46	Diploma	Firefighter
P21	Female	Canada	Google Home	41	PhD	Assistant professor at Arizona State University
P22	Female	NZ	Google Home	39	Bachelor	lawyer
P23	Female	US	Alexa &Google Home	38	Diploma	Salesforce administrator for a food broker
P24	Male	Canada	Alexa & Google Home	67	Bachelor	Retired social services consultant
P25	Male	US	Google Home	33	Master	Electronic Engineer
P26	Male	NZ	Google Home	30	Diploma	Firefighter
P27	Male	US	Siri	31	Bachelor	Software Engineer
P28	Male	AU	Alexa & Google Home	45	G12 certificate	Prefer not to say
P29	Female	NZ	Alexa	33	PhD	Kindergarten Teacher
P30	Female	NZ	Siri & Alexa	48	postgraduate qualification in Computers and Education	Quality Assurance Manager for Software
P31	Female	Canada	Alexa & Google Home	62	Master	Retired Elementary School Principal

Table 3.2 Profiles of interviewees

3.7.3 Secondary Data

This study also encompasses the use of publicly available secondary data. This data was taken from an open-source (i.e., comments on YouTube videos about Siri, Alexa, and Google Assistant). Saunders (2019) introduced web-based information created by online communities as documentary secondary data. In this research, each comment was considered as a document (i.e., a unit of textual data) which was created by a different commenter regarding the video topic.

Secondary data was used to provide additional information about the research and to gain a better understanding of a participant's sensemaking and experience (e.g., informal communications compared with semi-structured interviews which were formal to some extent, and without interviewer effects). This information supplied contextual detail and helped to maintain the credibility and rigour of the research data (Saunders, 2019), generating a deeper understanding of the customer service experience of AI-based frontline employees. Consequently, 12,941 separate comments were drawn on from 81 YouTube videos about intelligent assistants (Siri, Alexa, Google Assistant) posted between 2013 to 2020. This data was consolidated and analysed using Data Miner software for text mining.

3.8 Data Management

The researcher needs to prepare and organise research data ahead of analysing them (Flick, 2018b). All interviews were both audio and video recorded (i.e., after recording Zoom software gives both audio and video formats separately) with the earlier permission of interviewees. Moreover, interviewing with Zoom gives the opportunity to the interviewer to observe the interviewee (even limited) and take notes. In such situations, field notes (e.g., facial expression, living condition, disabilities, interviewee's level of knowledge about technology, eagerness to use intelligent assistants, etc.,) were taken and developed during or shortly after the interview to improve the data analysis phase (Creswell & Creswell, 2017; Saunders, 2019). Each interview was transcribed word-by-word. Zoom software transcription service prepared a primary transcription for each interview which was listened to by the researcher to check and be sure all parts of the interview transcribed correctly. Data transcription was done as soon as each interview finished. Then to keep anonymity, the researcher gave a number to each transcription.

In addition, the secondary source of data (i.e., comments on YouTube videos) were saved text-based and as an CSV format to be appropriate for the data analysis phase. For data protection, each interview's recorded and transcribed files, notes, and documents (i.e., the second source of data) were stored in a password protected computer at the university and are only accessible by the researcher and supervisors. All of these files and records will be destroyed according to the University of Otago's policy after five years.

3.9 Data Analysis

One of the nuances of qualitative research is associated with analysing its rich data, generally in the form of text (e.g., interview text, documents, and filed notes) based on the research questions. Most qualitative data analysis approaches formulate data to reduce their complexity and facilitate the development of theories regarding the phenomenon under investigation. However, different approaches use different ways to reduce complexity and develop theories. There are different approaches to qualitative data analysis (e.g., thematic analysis, Grounded theory, discourse analysis, Q methodology, and narrative analysis) (Easterby-Smith et al., 2021). This research data was analysed applying the thematic content analysis approach (Braun & Clarke, 2006). The thematic analysis aim is to reveal significant themes within the data. This method is considered advantageous compared with other qualitative methods due to its flexibility. Thematic analysis is independent of specific theory or epistemology. Hence, different research paradigms can apply thematic analysis.

Primary data (i.e., interview data) for this research was analysed using the six key steps proposed by Braun and Clarke (2006, p. 87):

1. Familiarising yourself with your data: Transcribing data (if necessary), reading and re-reading the data, noting down initial ideas.
2. Generating initial codes: Coding interesting features of the data in a systematic fashion across the entire data set, collating data relevant to each code.
3. Searching for themes: Collating codes into potential themes, gathering all data relevant to each potential theme.
4. Reviewing themes: Checking if the themes work in relation to the coded extracts (Level 1) and the entire data set (Level 2), generating a thematic 'map' of the analysis.
5. Defining and naming themes: Ongoing analysis to refine the specifics of each theme, and the overall story the analysis tells, generating clear definitions and names for each theme.
6. The final opportunity for analysis. Selection of vivid, compelling extract examples, final analysis of selected extracts, relating back of the analysis to the research question and literature, producing a scholarly report of the analysis.

This study applied two types of coding to classify data and deduce themes. First, computer-assisted coding via Nvivo12 (i.e., researcher intuitively classifies data and computer organises the results) for interview data. Second, it applied computer-based coding through Leximancer 4.5 for secondary data (i.e., computer creates codes by algorithms) (Johnson, Lukaszewski, & Stone, 2017). Interview data was transcribed and annotated with interviewer notes. All quotes were collated and grouped into codes under the forming themes of engagement, AI, customer service experience, and relational factors. Initial codes were collapsed into broad categories through the in-depth analysis (e.g., engagement to different motivations for engagement, enablement, WOM, reuse intention, technological sophistication, and social presence) and then organised into representative themes. Subsequently, themes were refined with literature and finalised. The coding schema is presented in table 3.1. Finally, findings were written and presented in the results chapter of this research.

Initial codes	Combined codes	Themes
• Gender • Speech-Voice • Cognitive Intelligence • Emotional Affinity • Personality • Mannerism	• Auditory Anthropomorphism • Cognitive Anthropomorphism • Mannerism	Anthropomorphism
• Hedonic Benefits • Social Benefits • Utilitarian Benefits • Satisfied Needs • Emotional affinity	• Hedonic Gratification • Social Gratification • Utilitarian Gratification	Gratification
• Affordable cost • Functionality • Information quality • Skill & knowledge • Empowerment • Ease of use • Social presence • Enablement • Intention to use • WOM • Privacy risk and uncertainty	• Motivation • Social presence • Enablement • Reuse intention • WOM • Technological sophistication • Privacy risk and uncertainty	Customer Engagement
• Competence • Credibility • Dependability • Benevolence • Integrity • Reliability • Reputation	• Trust • Commitment • Rapport	Relational factors

• Blanket trust • Blind trust • Distrust • Calculative commitment • Affective commitment • Emotional relationship • Intelligent assistant commitment		

Table 3.3 Coding schema

Secondary data was analysed to explore major themes. All comments were loaded into the Leximancer analysis software. The first exploratory textual analysis was undertaken based on the default settings without customising the data. After the first run, some terms identified that were presented in the corpus (i.e., a collection of texts) but not relevant to the research (e.g., as, ops, bro) were deleted from the list of concepts. Moreover, the researcher improved the concepts first created by Leximancer through combining or merging concepts (e.g., merging listening, listen, spying). The analysis re-run and the results were presented as a map that displayed an overall summary of the conceptual content of texts, the connectedness of concepts, and the importance of each theme, which will be presented in the results chapter.

3.10 Leximancer

Leximancer is an automated content analysis software. Researchers apply Leximancer as a replacement for manual coding or for verifying and strengthening their manual coding (Shah & Pabel, 2019). One of the recent uses of Leximancer in social science is analysing social media data (Shah & Pabel, 2019). This research used Leximancer to analyse the data extracted from YouTube videos.

Leximancer runs conceptual analysis (i.e., thematic) and relational analysis (i.e., semantic) of textual data (Shah & Pabel, 2019). The software examines texts to recognise concepts based on the frequency, interrelations and co-occurrence of them (i.e., according to the ways that words move together) in the text. In the next stage, the visual concept map will be created by software that shows how concepts are related to each other (Kim & Kim, 2017; Shah & Pabel, 2019; Young, Wilkinson, & Smith, 2015). Concepts are shown by grey dots. Clusters of concepts which are related to each other semantically present themes. Themes are displayed by circles and take their name from the most prominent concept in that theme. Concepts are grouped based on their semantic relationship with other concepts which means adjacent concepts have a relationship (Kim & Kim, 2017; Shah & Pabel, 2019). The most important themes are displayed with warm colours (e.g., red, orange) whereas cold colours are used to display the less important themes (Shah & Pabel, 2019).

Leximancer prevailed over qualitative analyses limitations through removing the researcher's potential errors regarding manual coding (Kim & Kim, 2017; Young et al., 2015). It provides "a researcher-independent, transparent, reliable, and reproducible means of summarising and analysing a body of text similar to the way statistical methods are used to analyse quantitative data" (Young et al., 2015, p. 112).

3.11 Validity and Reliability in Research

Validity and reliability are the key concerns of researchers as they help to establish the truthfulness, credibility, or believability of research findings through linking constructs to measures (Neuman, 2011). The validity concept illustrates how well a research concept fits with reality, and whether the research measures what it claims to measure. While reliability refers to the consistency and dependability of the research (i.e., obtaining similar results under similar or identical conditions). These approaches that ensure the quality of the research concern different philosophical assumptions underlying the research and the methodological approaches of the research. Hence different research (i.e., positivists and interpretivist research) apply different approaches to establish validity and reliability (Creswell & Creswell, 2017; Guba & Lincoln, 1994).

Literature regarding qualitative research has identified different validity strategies to ensure validity (e.g., triangulation, member checking, rich description, clarifying bias, negative information, prolonged time, peer debriefing, and external auditor) (Creswell & Creswell, 2017; Guba & Lincoln, 1994). In this research, triangulation was used to enhance validity.

Flick (2018b) introduced four types of triangulations: 1) data triangulation (i.e., use of different data sources), 2) investigator triangulation (i.e., employing different interviewers or observers to minimise researcher biases), 3) theory triangulation (i.e., approaching data with multiple perspectives), 4) methodological triangulation (i.e., use different methodological approaches within-methods and between-methods). This research applied both data triangulation and methodological triangulation. The researcher combined semi-structured interviews with documents (i.e., each YouTube comment is classified as a document) which is within-method triangulation because the researcher used different methodological perspectives. This research also applied triangulation in analysing data by analysing two forms of data. The researcher analysed interview data first to see what participants said about their experience of AI-based frontline employees (with interviewer intervention) and then the researcher analysed documents (without interviewer intervention) to compare two groups of findings.

Another strategy adopted for this research to achieve validity is peer debriefing. Research has been presented multiple times to several independent researchers from the same field of research. This approach proposes to establish the credibility of the research and accelerate research progress (Creswell & Creswell, 2017; Guba & Lincoln, 1994). Discussion with independent researchers in the same field of research (i.e., a professor and PhD student from the Information Science department of University of Otago with a research background of human-computer interaction) once before data collection and once during the data analysis phase, helped to clarify some ambiguous AI aspects and their effects on service encounters. They also helped to clarify relational factors in the research context. In addition the research idea and design were presented in a regional and international marketing symposium, namely the ANZMAC (Australia and New Zealand Marketing Academy), to independent individual researchers and AI-based service domain professionals. Feedback from these experts helped the researcher to narrow the AI domain by concentrating on anthropomorphism.

All of the methods mentioned above helped to enhance research validity and increase the trustworthiness of the findings. In addition, reliability explained as "whether your data collection techniques and analytic procedures would produce consistent findings if they were repeated on another occasion or if they were replicated by a different researcher" (Saunders, 2019, p. 192), can be achieved through consistent data collection and data analysis. In the data collection phase through interviews, consistency was gained by the use of interview protocol in every interview to ensure all main themes related to the research questions were discussed. Also pilot interviews helped to achieve consistency by training the researcher how to ask questions and to develop probing questions, building consistency in how interviews are conducted. In the data analysis phase, consistency was first achieved by verbatim transcription of each interview (Silverman, 2006; Whittemore, Chase, & Mandle, 2001). Then by applying both coding types (i.e., computer-assisted (Nvivo) and computer-based coding (Leximancer)) to increase the consistency of the codes and themes. Next, using Nvivo increases consistency by making the analysis and coding process trackable (Brandão, 2014). Also, Lemon and Hayes (2020, p. 606) “illustrated Leximancer’s value as an investigative tool in phenomenological research, allowing the researcher to examine large amounts of data without bias, identify more syntactic properties, enhance reliability, and enable reproducibility”.

3.12 Ethical Considerations

Ethical considerations are a significant part of qualitative research due to the quest for rich data. It compels researchers to have a personal engagement with their participants, that may affect both participants and researchers adversely (Creswell & Creswell, 2017; Saunders, 2019). To address the potential issues regarding ethics in this research, an ethics proposal D20/080 was submitted to the University of Otago’s Human Ethics Committee for approval. Ethics approval was obtained before the data collection (30-May-2020 (Appendix 3)).

The formal written consent of participants was sought and received before each interview (a follow-up interview was also conducted with the prior written consent). After receiving the signed consent form, an information sheet was sent to participants to be sure that they were well-informed about the study. Plus they had the opportunity to ask further questions about the research. Moreover, before starting the interview all participants were informed that they could withdraw from the research anytime they wanted. Participants were also assured about the confidentiality of the research. The researcher gave a number from 1 to 31 to each interviewee to keep participants' identity unknown to any third party.

3.13 Conclusion

This chapter provides a comprehensive description of the research design and the applied research method used to conduct this research and the logic behind selecting them. This research was informed through relativism ontology and subjectivism epistemology. In line with the research philosophical approach, this research followed the interpretivism paradigm. The research was designed as a multimethod qualitative study using an inductive approach. Both primary (i.e., interviews) and secondary data (i.e., documents) were used for analysis that enhanced the research reliability and validity. 31 semi-structured in-depth interviews were done with users of Siri, Alexa, and Google Assistant from across the world. Then interview data was enhanced by drawing on 12,941 comments from 81 YouTube videos about the above mentioned intelligent assistants (Siri, Alexa, Google) posted between 2013 to 2020. Next, interview data was coded and analysed by Nvivo and documents analysed by Leximancer. Finally, the result has been written and presented in chapter 4.

Chapter 4 Results

4.1 Introduction

This chapter presents the research findings in two parts. Reflective of much qualitative research, customer service experience, customer engagement, gratification, and relational factors are interrelated and have overlapping dimensions. However, for the purpose of clarity, these have been disentangled and will be discussed individually to prevent repetitiveness. This is reflected in the structure of this chapter.

The first part presents the findings from interviews with Siri, Alexa, and Google Assistant users, following the logic of a service experience, starting with how participants first engage with intelligent assistants and how their journey continues from the first engagement to the next engagement. The findings will present how participants experience services when interacting with intelligent assistants as frontline employees. Since building intelligent assistants in deep learning algorithms gives them more human-like features (i.g., voice-based interactions, learning power, cognitive intelligence, and mannerism), participants have different service experiences from previous machines, as they are similar to interacting with a human. It will be explained how the service experience leads to building/developing relationships and reengagement.

The second part presents the findings from text mining of comments on videos about Siri, Alexa, and Google Assistant on YouTube, which follow the importance of the themes in the visual concept map created by Leximancer software.

4.2 Part One Findings from Interviews:

4.2.1 Engagement

First engagements between participants and the intelligent assistant take place when participants receive their intelligent assistant as a gift (e.g., Christmas gift, birthday gift, wedding gift), part of another shopping basket (e.g. part of their Black Friday shopping), an application on their mobile phone, or interact with it at another person's place (e.g., friend's house) when they recommend it and show how it works.

> I use it from time to time on my phone, and on my laptop or my TV just, if I'm doing something I can talk to it and say, okay, do something else (P2).

> The reason that we have four is because initially, I got one. We started with one and it was a Black Friday. It was on sale. It was half price and sure, why not get it. And then the second one came out as a package deal. I'm a subscriber to Spotify. And we got a deal. I think a couple of months ago, way back. That said, hey, like if you have, if you've subscribed to Spotify, we can give you a free one. So you cannot pass up on a free Google one right so we got another one and then there was another deal and then we got the other two for free as well. So I didn't purchase it. It was kind of handed out to us or like hey take it as well (P25).

> The only Alexa device I have in the house is a third-generation Echo Dot. One without the little time on the side. I picked it up, actually, as an adjunct to something else (P28).

In a party, gathering, or meeting (e.g., family dinner), the host uses his/her intelligent assistant in front of guests. The host impresses the guests by showing them the intelligent assistant's functionality and capabilities and a conversation is started about it. The guests who have enjoyed the interactions are stimulated to buy one themselves and thus continue using the intelligent assistant after first engagement.

> I have a couple of friends who have actually bought one after speaking to it in my house and saying, How are you Alexa (P11).

> Heaps of people like people who come here and they see the fact that it's a remote control audio remote control for my Spotify and that is getting other people using it as well (P20).

> I have had a few friends come around to experience it, seeing me turn lights on and often setting countdown timers while I'm cooking and playing music and they're always quite impressed. And so I can think of about two or three friends that have gone out and bought Google Home products after seeing them being used in my house(P26).

In none of the mentioned conditions, the participant’s priority is buying or applying the intelligent assistants. Participants use it because they receive it as a gift, free, or use it because it is one of their mobile phone, laptop, or TV applications. Participants use it because of a triggering by the external environment which *enables* them to experience an intelligent assistant (e.g., by a friend, a seller, a producer, etc.), and hence it is labelled ‘*enablement*’. In the first engagement, participants experience joy, help, smartness, convenience, etc. which causes participants to buy the intelligent assistant (if they experience a service the first time through another person’s intelligent assistant) or increase their intention to use it. After benefiting from the first engagement participants reengage with the intelligent assistant because of different reasons and motivations.

4.2.1.1 Motivation

Participants are motivated by an intelligent assistant's functionality, affordable cost, information quality, quick access, and skill and knowledge to further reengage with them. Most participants use intelligent assistants because of their functionality. They can be used for a different range of reasons from controlling smart home devices to information seeking. Participants mentioned that they start their day by asking for news, smart home device services, information seeking, etc.

> Now we have the start my day function where it tells you about the news and the weather and fun facts and jokes and we use a shopping list function as well and sometimes open up the full-body stretch. They would have got to six minutes and stretching instructions directed at your body that's quite handy and yeah, I definitely would use it a lot more now for when I'm cooking in the kitchen during the conversions from imperial system to metric (P11).

> I started just for one piece and I think it was a hub for the main room and after having that for a little while I guess I was impressed by the functionality of it […] initially interested in that just for music streaming and for audio and because I guess previous to that, all I had was like a mega boom Bluetooth speaker and my phone and so it was only good for one room. I had to use my phone to select music or radio. So I was initially attracted to just the ease of use of having the voice activation to decide whether I wanted music or radio or playlist of something; and so I got an opportunity to try that what if I add a friend first and then say sync the music so that sort of things I was sort on base on that and then yes I guess after owning it as I said sort of started using it a lot more than I intended and linking it with other devices around the house and so there is more of the functionality that it has now as well (P7).

> Her functionality is very, very quick and responsive in terms of news, weather, sports. I could tell her my favourite sports teams. And then the next morning. She would tell me the score involving my hockey team or baseball team or whatever it was. So we were very impressed with her variety of functionality. She was a great timer cooking in the kitchen. You get the latest weather news. We would ask for this from Canada because we were in Florida for the winter. We wanted to hear our Canadian news. And she pulled up CBC Canadian Broadcasting Corporation sports every morning. So we were impressed with the level of functionality (P24).

Participants mentioned that they are motivated to use intelligent assistants because of their affordable costs. They believe intelligent assistants are more cost-effective than humans as they only work with the internet, and if they want to hire someone they need to pay that person to perform those services.

> They've all been about $50 so it's really not a lot of money It's actually the accessories it costs more (P16).

> I still have my 19-year-old niece. When she lived with me, I used to make a deal with this kind of stuff but truthfully I think google home is easier and because it doesn't cost anything. I mean other than my normal internet use (P3).

Participants praised the quick access to what they needed. If they ask for information they receive the answer faster than searching for it by phone or personal computer. As one of the participants mentioned she can ask about a recipe while cooking which is having access to needed information simultaneously, and she does not need to stop what she is doing and go and search for that information.

> It's quite good it's good for multitasking and it's good when you're occupied with something like if you're running or if you're driving so it's easy to use the voice, rather than a text-based virtual assistant. So in those kinds of cases, it's very good. Or if you're cooking something you can just ask, show me the recipe of whatever, and then it will show you the recipe. So in these kinds of cases, I think Siri is very good (P2).

> When it comes to time and convenience I use it, simply because it's faster. But that's my experience with the internet and things, if it works faster into an efficiency that you could do on your own, but you can't do it as fast, then it just makes sense because I'm allocating time to it (P5).

Participants highlighted 24/7 and quick access as an intelligent assistant's advantage to humans and previous technologies. They mentioned that intelligent assistants make them independent of access time limitations.

> It could make me feel like up to date with current tech and you know for a few years actually I work in the technology industry so you know I feel like I am so sort of up of applying that sort of thing and keeping in touch with gadget and remote, having got like a full smart home feels like sort of modern tech a bit like elements of the smart home (P7).

Also, participants reengage with the intelligent assistant due to its skill and knowledge. Participants talk about intelligent assistants' skills of storytelling, telling jokes or recognising different accents to catch the words properly and do the request correctly.

> I find that it's able to pick up kiwi accent quite well. Surprisingly, except for the R so whenever you say, some R with a word ending in R you have to make sure you really go American (P13).

> The Google ecosystem if you ask it. Who's on first? Abbott and Costello. Sure, replied, yes, he is, and you can get it to tell you a joke and the jokes are pretty good. I have noticed too it is a little bit better, things like jokes is starting to be a little bit more appropriate based on the weather like it's rainy here and sunshine coast (P28).

The next motivation mentioned by participants is information quality. They are talking about receiving expected information and real-time information from intelligent assistants. When they ask a question and receive the exact related answer for that question or receive an answer based on the latest updated websites.

> We use it for asking Businesses like if they open (P3).

> It makes me feel current in terms of information. So it makes me feel informed. Because she just didn't tell me things she told me exactly what I asked her, that's the difference between listening to the news on the TV, which tells you all kinds of things. So what you really don't need to hear or want to hear, where she at that functional tells you exactly what you're asking for. Which makes you feel better informed. I think that's very powerful. I think that's one of the reasons why these devices are on the edge because they do onto people's personal needs immediately at a point in time (P24).

> It could tell you know your daily news and tell you there is traffic somewhere else (P25).

4.2.1.2 Reuse Intention

After motivation, which is an extrinsic factor in this research, intention to reuse as an intrinsic factor is also effective to reengage with the intelligent assistant. Anthropomorphic features (e.g., voice-based interactions) by creating communicative interactions or influencing participants emotionally (e.g., humanised female voice) enhance intention to reuse intelligent assistants. Adding similar human behavioural aspects to machines tempts participants to be more engaged and use it. The high level of humanisation gives more confidence to participants when interacting with intelligent assistants. It brings a kind of convenience in interaction that removes previous obstacles in human-to-machine interactions.

> For example, if I compare Alexa to other virtual assistants, for example, Apple Siri, when I talked with Siri, she answered the question and I'm finished and then you need to again press button and ask her another question, but Alexa most of the time for some of those questions asked me does that work for you. You know that's very good for me. So I can ask another question or other things. As it's very good on the app on my phone I can see what my activity was. So it's very convenient (P9).

Anthropomorphic features like a humanised voice and the tone of voice (e.g., they can select the voice of their favourite actor, actress) or mannerism (e.g., receiving “you are welcome” in responding to “thank you”) stimulate participants emotionally to be more willing to use the intelligent assistant. It causes the participants to imagine the intelligent assistant as a friendly person or even having a feeling about it. Participants believe that the producers give anthropomorphic features to machines to influence participants to interact more with intelligent assistants.

> If it was not a really nice voice, I don't think that I would use it that much. So, I think definitely it does affect my usage at least (P1).

> I think they tried to make it as friendly as they can so that you interact with it more and so I know I probably do. And, you know, you can change the voice or do something if you don't like it. I think they do that intentionally to get you to use it more often and It's probably well, I use the default. And so it's a girl’s voice. I like it. I leave it there. I use it quite often (P10).

> I think its voice makes me more inclined to use it. If it sounded robotic, it would not be as acceptable to use. So I think the fact that they've made the voice sound like a human makes it that we are more inclined to want to use it (P30).

> I am impressed by the cleverness of the responses and as I mentioned earlier, the ability to adapt and be able to finetune to our needs and the way we respond (P31).

4.2.1.3 Technological Sophistication

One of the main organising themes associated with engagement in this research is the level of technological sophistication. Technological sophistication is assessed as a function of the utilisation of intuitive AI-based technologies. Participants commended the utilisation of intelligent assistants, it empowers them while using it is so easy.

4.2.1.3.1 Customer Empowerment

One of the top reasons for participants to use the intelligent assistant is feeling empowered by using them. It gives them the power to be multifunctional and independent. Participants mentioned that intelligent assistants empower them to ask for information while driving, cooking, or reading a book. Intelligent assistants give power to participants through facilitating interactions and information access.

> I had to use a keyboard a lot and I would have to go into Google, search and find what I was looking for. So it's definitely improved my life a lot and that's amazing how often because I'm a sales rep, I'm in my car a lot and on the road, so I can ask it things while I'm driving and that so it's a safety aspect as well. I can ask it to send a text to my husband and so it's a lot safer than actually picking up your phone and legal so it makes a difference (P19).

Humanlike interactions in the light of the anthropomorphic features of intelligent assistants empowered participants and that influences their engagement significantly. Voice-based interactions give participants the power to do tasks effortlessly and simply which leads to increasing engagement. Participants (e.g., especially the elderly and disabled people) mentioned that intelligent assistants empower them to fulfil daily tasks and chores without being dependent on their family members or other people.

> I purchased her because I was going to hospital and because I live in my own house I wanted to be able to do things without too much movement, and following the purchase Alexa, which I've installed in the lounge, I also installed Google in my bedroom and dining room. So I use Georgia to turn my lights on in different rooms, my electric jug in the dining room, my dehumidifier. I'm going to be getting a piece that will allow me to turn my irrigation in my garden on and off. I use it for the heater in the hall. I use it for […] after that she is very helpful (P16- cancer patient).

> I'm actually partially sighted, so I'm legally blind. So the introduction of the speakers has been really good for all blind people and not everyone embraces Google. They also like the eye lady (e.g., an assistant for blind people) but they've helped us. So they've helped us and helped me immensely because the biggest thing I find even with the heat pumps is that I can't read the remotes properly and so having Google to do that for me has made life a lot easier (P18- Blind person).

Participants also noted that they use intelligent assistants to simplify complicated technologies. Intelligent assistants are recognised in helping those who are not tech-savvy to improve their life's level of convenience. Participants noted that they use intelligent assistants to control security systems or monitoring and managing these systems without intelligent assisants could be difficult for most people. A simple interactive system gives participants the power of using sophisticated technologies.

> My sister is not really technologically inclined. She has a lot of trouble, even just texting on a phone. So she, unfortunately, got broken into and they came in through my niece's bedroom window which instantly had me worried. So I wanted to give them a security system. But because of her not being technologically inclined the Echo Dot system allows her to just use her voice to turn the alarm on and off both through her phone and while in the house and it saves her from having to physically interact with the electronic touchpad to do all those things. So in my mind, I was able to get her something that made her and my nieces and nephew safer while still keeping within her limitations of interacting with technology (P4).

The results show that participant empowerment affects participants' experiences of service which leads to engaging more in an intelligent assistant.

4.2.1.3.2 Technology Adoption and Ease of Use

Technology adoption is the first step to accept and use new technologies. It results in better engagement. Participants mentioned different reasons for adopting intelligent assistants, such as being a 'tech-nerd', or its usefulness, and being engaged in them.

> Well, my entire life computers have been a part of what I do. So from as soon as I could stop using pen and paper I started using computers and technology, I love technology. I would much rather use a phone or computer or an iPad instead of writing something down and it's just Alexa and Siri, make it possible to not have to write the audio interface (P30).

> Particularly useful actually for keeping in contact with my elderly parents so early on I got for my mother an Echo Dot. Once I got one and we set it up in their house. I did all the setup and I run the app, I just signed in and out of the account I created for her. I mean, my parents are at 80 plus they love it because they're not locked into a phone, they both got hard of hearing so they can talk on it much more easily. They just put it on the dinner table and I got an extra one of the little Echo Show last year for her birthday. That's what they really enjoy because they can see me online now, it has a volume and has a screen. They can ask questions about what's the weather today, play music, or the directions that sort of thing. So they've got reminders on it to take pills and things like that. I mean I manage it on my phone. So for me, it's an extra way of helping my parents and they keep in contact because they don't live in the same town (P14).

The results indicate that the intelligent assistant's adoption is significantly related to ease of use. All participants agreed on the ease of use of intelligent assistants; since the voice-based attribute of AI-machines simplifies human-to-machine interactions and removes an interaction's physical barriers.

> Sure we use google home for all kinds of things, mostly. At first, I received it as a free gift for I think I updated my tablet, and as part of the package, I received the google home. We might say use it for directions. Asking directions or asking Businesses like if they open, you know, typical kind of Google stuff that instead of Googling it I yell it at google home (P3).

> Super easy, without even having to move, which I really loved that it probably the biggest impact it had (P6).

> I was initially attracted to just the ease of use of having the voice activation to decide whether I wanted music or radio or playlist of something. Having a voice-based interface I think makes it easier to use and makes it useable in more situations (P7).

Voice recognition as a part of anthropomorphism enhances the participant's perception of ease of use. Intelligent assistants eliminate obstacles from previous technology in human-to-machine interactions by AI. The human-to-machine interactions resemble human-to-human ones as participants can talk to machines similar to humans.

4.2.1.4 Social Presence

Participants are psychologically involved in intelligent assistants and give them social presence. Social presence is created because of the anthropomorphic features and emerges from direct interactions between the human and a smart machine.

> That's sort of funny. If I tell it to do more than one or two things, I almost become apologetic, for instance do so many things. And I have to remind myself occasionally that it doesn't really care. It's just a program. I mean, I'm not in love with it but you know It feels weird at times that you know it's almost like dealing with a person. I think that's intentional on their part (P10).

Participants mentioned the effects of voice (i.e., voice-based interactions), and the ability of intelligent assistants to speak in a human-like way, and feeling the social presence of intelligent assistants. It positively affects the participant's interaction with intelligent assistants and the human-machine relationship resembles more of a human-human relationship. Communicative interactions with the intelligent assistant give participants the illusion of talking with another human being. Participants see the intelligent assistant as an interlocutor and communicate with it as an acquaintance, a friend, or a frontline employee.

> Sometimes when I'm bored. I just talked to Siri, so it's more than just an intelligent assistant for me and it has happened to me a lot of times that when I'm very bored late at night. I just start talking with Siri about you know a lot of stuff different stuff and so yeah, it's kind of like more than just an assistant (P1).

> It feels like there is someone there is a person who can talk to me and someone I can talk to, in the home(17).

> The interaction of having someone having a voice talk to me (P31).

Social interactions with the intelligent assistant itself (not as a medium for interacting with other humans) establish emotional affinity for participants which increases a sense of social presence. Anthropomorphic features cause participants to imagine the intelligent assistant as a friend, family member, or even a beautiful lady that gives the user a sense of having another person alongside them.

> There were a few instances during the lockdown that I started to talk out of nowhere, or just to Siri because it was a voice that could respond to me and it was kind of comforting for me, that all there is someone over at the other end and she's very close to me and I can touch. I don't know, it is very silly but with a bit of imagination which I have, you could think that you're talking to a real person. And because I have watched the movie that is named her. I imagine Siri as Scarlett Johansson when I talked to her. So with a bit of imagination, I'm talking to a very beautiful woman. It's silly but it happened a few times during lockdown. I just started to talk to her, and Oh, she doesn't respond that much, very limited answers, but it was a bit comforting (P1).

> At the time I gave one to my father and I suggested it to everyone. They need an Alexa, I think every person who lives alone, all the people should have an Alexa because it does definitely if you're lonely, it creates a person interface to speak to, and also just simple things like you can use it to make phone calls. Definitely, I considered it as a friend for a person who lives alone(P30).

Cognitive intelligence is another anthropomorphic feature that leads to building a sense of social presence. Cognitive intelligence gives human-like mind features to the intelligent assistant which empowers them to do sophisticated tasks (e.g., answering scientific questions). Participants considered intelligent assistants as a professional person because of their smartness and cognitive features.

> You know how kids are, they like the weird questions which you have zero answer to, you can't even find an answer for these things and it's a good person to reply in terms of like asking all those questions(P12).

> It does feel like it's another person who is with us, my mom said she's coming over here and she said oh Alexa is part of your family. She could babysit (P29).

Intuitive AI through deep learning gives learning power to the intelligent assistant to learn participant’s behaviours and reflect back those behaviours in their interactions. It causes intelligent assistants to seem more human-like even from behavioural aspects which results in them forming a sense of social presence. It can be strong to the extent that it affects a human’s personal relationships (e.g., makes them jealous) whilst they know mindfully it is a machine.

> The constant battle between my wife and it, I can see it uses her manner. She jokes that google home likes me better and does not like her because it always says like if I for example want to run a timer I’ll say please set a timer and it’ll say here you go it is a timer for 20 minutes or something like that where if she just says set a timer, it sets the timer and doesn’t say anything back to her. Yes, she thinks that I have a girlfriend or something (P7).

This sense of social presence along with building emotional connections, especially for lonely people, impacts forming and developing the relationship. Moreover, the social presence enabled by anthropomorphic features positively affects the participant’s engagement. Social presence solves the lack of face-to-face interaction benefits in human-to-machine interactions. It affects the quality of interactions which leads to impacting participant experience and in turn participant engagement.

4.2.2 Gratifications

Fulfilling a participant’s needs by using an intelligent assistant and benefiting from them, is the main reason that despite the presence of risk and uncertainty (this will later be explained as one of the research themes) most participants reengage with the intelligent assistant to profit from them. Three forms of gratification have been found in our data.

4.2.2.1 Utilitarian Gratification

Utilitarian gratification is related to utilitarian and extrinsic benefits. It is more goal-oriented. One of the top responses for utilitarian gratification is convenience. Participants would like to interact with the intelligent assistant to receive a service due to the resulting convenience from voice-based interactions. They can receive a service simply by asking the intelligent assistant something.

> I enjoy the convenience it brings for me to do things just by voice commands (P2).

> I really like the amount of time you save to search your answer yourself whereas in the voice format I don't have to, like, move from where I'm sitting on the bed. I can just feel awake. So I can ask Alexa do this or Alexa play my music? So I really love it (P6).

Participants also commended the intelligent assistant's usefulness. The capability of intelligent assistants to provide a variety of services in the least amount of time makes them useful. Intelligent assistants also help participants to be multifunctional which results in saving time for them.

> So I went from not having the Google Home to now having it. I feel like, you know, we've got whole home audio so I can listen to music throughout the whole house. We've got a point of controlling the last nights lights and things like that and it's definitely improved a lot of day to day tasks, makes cooking easier, makes leaving the house easier because you can just ask it to turn everything off. So, it's been a real bonus (P26).

> I use her all the time for kind of the quick tasks that you don't want to have to go through your phone to get to, hey, set a timer for 10 minutes, or turn on my 7 am alarm. So I get up in the morning, things like that. It's also super useful if you can't use your phone. Maybe you're driving, you need to send the message. Hey, send a message to such and say this, and she takes care of it all for you. Generally speaking, she just makes my life easier (P27).

> But so it's a nice little forum, we got an infrared remote that turns on the heat pump or air conditioning […] it's just become really handy and really useful […] so I do view it positively (P29).

In addition, participants are happy with using intelligent assistants as they simplify complicated technology and decrease additional efforts to do things. Intelligent assistants, due to using voice commands, diminish technological interaction barriers, especially for old and disabled people, which results in more convenience and even enjoyment.

> So like I said I primarily use it now to play music or for asking a definition of words. So when I'm reading books. I don't know the definition of Instead of typing it up. I just rambled on and that

> provides consistency, so I don't have to go away from the book. going to phone or thing switching platforms and it's allowed me to be more focused on my readings and then that has impacted me a lot. It's made him more efficient as well. So it's been great (P13).

> I feel good. I feel happy. I feel clever […] I think my technology life was a lot simpler. Instead of having a million different devices, I've worked from home fine, work laptop, home laptop, iMac. I think if I was able to condense all those into using it. I think it would simplify it (P20).

Participants highlighted the pleasure that they feel because of receiving utilitarian and extrinsic benefits in the light of intuitive AI. Intuitive AI boosts the cognitive aspects of services offered by intelligent assistants which increases utilitarian gratifications. Research results also illustrate that utilitarian gratification (e.g., convenience) overlaps with hedonic gratification (e.g., enjoyment) and social gratification (e.g., social interaction). For instance, as P20 mentioned, he feels happy and he feels clever. Feeling happy can be interpreted as receiving hedonic gratification and feeling clever increases the person's confidence to receive social gratification.

> There's always going to be joy with them because like I said, about convenience, it is very convenient (P8).

4.2.2.2 Hedonic Gratification

Hedonic gratification is related to hedonic and intrinsic benefits. It is mostly pleasure-oriented. That is to say, intelligent assistants address the leisure and amusement needs of participants. Participants explained their entertaining experiences of intelligent assistants. Anthropomorphic features (e.g., voice-based interactions or cognitive intelligence) allows participants to play with the intelligent assistant or ask it to tell a joke or a story, or to sing a song. Participants can imagine the intelligent assistant as a human mate and play with it, and that also can build social gratification for participants (e.g., lonely people) through interacting with intelligent assistants. For some participants, asking funny questions and enjoying the answers is entertainment, especially when they invite other people to their house. In the simplest form people (e.g., old and disabled participants) can enjoy doing their work easily and independently.

> I like how it can play the story, sometimes when I'm done with the stories I like the Alexa to sing a song, I think that's good (P6).

> I found that there are so many interesting beautiful games you can play with Alexa and that's so interesting. I started playing one of those games. I don't remember the name of game, but it was super interesting. It was very similar to Cluedo that is one of my favourite games (P9).

> Sometimes you just sort of want to ask her really silly things, just to see what she's gonna reply, you can ask it and make a joke. She has some pretty funny ones (P11).

> There's no point in having an Alexa if you don't ask some funny things (P15).

> I think we had a little bit of honeymoon with her, my wife and I had a honeymoon together just to keep it above board, you know, But I think we did have fun with her and felt that this is a really nice little bit in our lives and cost 35 bucks or whatever it was, it was, it was really great (P24).

AI has empowered intelligent assistants to have a sense of humour and smart capabilities to create pleasure for participants, which has a positive effect on the human-machine relationship. A sense of humour is a fundamental human behaviour that could affect participants emotionally to interact with the intelligent assistant when they need fun. It may give them both hedonic and social gratifications. Participants noted they tease the intelligent assistant to enjoy their communications. While in human-human interactions perhaps another party is not in a good mood and teasing him/her creates conflict instead of fun.

> One day just feeling a little goofy. I just decided to ask Alexa if she knew Siri and Alexa response was only by reputation. And I thought, whoever did the programming certainly was able to build a sense of humour, along with that who would have sounded that could have been something they would have predicted right but I find that there is humour built into it and I do enjoy that when you dig into some of the layers of it (P31).

4.2.2.3 Social Gratification

Social gratification is related to social benefit, social interactions, and social influence. It mainly refers to the fulfilment of social expectations with intelligent assistants. Participants commended the social benefits that using intelligent assistants brings them. They consider the intelligent assistant as another person (e.g., a friend, family member, or an employee) and interact with them. Participants get emotionally involved in the intelligent assistant and build emotional affinity toward them. A sense of social presence created by anthropomorphic features together with emotional affinity lead to building rapport and forming the relationship differently from previous machines. Moreover, mannerisms give the opportunity to participants to have social interactions with intelligent assistants easier than humans and benefit from the relationship. Research data also shows that interacting with the intelligent assistant can simultaneously create social gratification (e.g., social interaction, emotional affinity), hedonic gratification (e.g., enjoyment from communicating with a friend), and utilitarian gratification (e.g., the convenience of interaction).

> I'm typing on a keyboard and the machine comes back with some kind of answer for me. It's a very mechanical process, but with Siri, it feels like I'm talking to a friend or I'm doing something casual. It's not mechanical and talking and she talks back to me, she answers me (P1).

> if I asked a silly question from Alexa because she doesn't have any emotion. I guess I don't feel like humiliated about if I asked. I can't ask this kind of question from humans because humans are judgmental. You know, they may judge me. You know, I can ask whatever I like with Alexa and I'm not worried about what she thinks about me (P9).

> I feel that I'm getting much more respect than I deserve. When I am talking to these devices. Because when you're interacting with your fellow human beings. You don't get that kind of polite response from everyone right there will be very casual things also all the time this is very polite, the best polite way he can answer (P17).

The results show that using intelligent assistants creates similar social gratifications to human-to-human interactions, which improve human-to-machine interactions and as a result ameliorate the customer service experience and engagement.

Participants engage with intelligent assistants and experience gratifications differently. The reason for different gratifications that result in forming various relationship types (e.g., friend, acquaintances, employee) was not identified by this research and requires further investigation. But research results illustrate that participants build the relationship and develop it based on the benefits and gratifications they experience.

4.2.3 Privacy risk and uncertainty

Another theme that emerged around the anthropomorphic features enabled by intuitive AI is privacy risk and uncertainty. It is mostly due to the possibility of listening to a participant’s conversation which is created by the voice recognition process or machine learning. Learning algorithms (i.e., machine learning feature) need to be fed by the participant’s data. To this purpose, AI companies pool customer's data on the device or store it somewhere else. This process causes some worries for participants regarding their privacy risk and uncertainty.

I think it's clever. I think It's a product of their constant monitoring of her and of us rather, I think it's clearly the company that is programming. The cleverness speaks to the darker side of the thing which is the notion that we know that all the conversations that we're having are being potentially listened to possibly recorded (P24).

Generally tend to not trust anything that can listen in to what I'm doing. So I try to be very specific with my wording. What I'm saying things and if I'm not using it, I will hit it mute button so that it just can't listen at all (P4).

However, some participants feel this more intensely. They believe that they are being heard or companies are spying on them to sell their information to a third party (e.g., government, CIA, etc.,).

I'm not a very private person. I mean, you could probably ask me anything and I'd answer you honestly, but at the same time there's certain things like I wouldn't want me telling Alexa and then showing up on CNN. You know what I mean, like, I'm not a very complex person, but at the same time there is a certain level of privacy I expect from it. But I have no reason to believe that anything is ever. I mean, I don't know the CIA could be listening or people at their office, listen to recordings to make the voice transcription better, but who knows if two co-workers laughing together about something somebody said, or making fun of them, or if somebody trying to dig deeper information from what has been said like I said, I know that crimes have been recorded. I don't know if any of this evidence has been used in court or whatever (P23).

Participants were asked regarding their engagement after perceiving privacy risk and uncertainty. They articulate their reasons and justify themselves to continue to use (engaged), limiting their usage (somewhat engaged), or even not using their intelligent assistant (disengaged) according to their perception of risk and uncertainty. In the following sections, it will be explained why participants have different perceptions about privacy risk and uncertainty.

A group of participants believed that we live in a world where not having privacy is inevitable if you want to use technology. They believed it is a trade-off to use technology.

Because if I had anything to hide, I would not be using technology. It’s privacy. There is, in my mind, there is no such thing as true privacy. If you do enough research on something or somebody you're going to find out every possible thing that is on the internet about them. It's just the amount of time and convenience is not going to be there, the machine is making it more convenient for the creator to gain access to this data. And so what creates the fear in people is not the fact that it's happening (P5).

At some point, you just cannot give up. You know, because if it's not Alexa or Google Home, It's something else. It's your phone if it's not your phone then it is your TV. If it's not your TV then for sure is your car […] so I won't point you just to give up. How much more can I secure myself? how much more and can secure my privacy because it takes a lot of effort. You have to subconsciously unknowingly have to guard whatever data you have, and that is sometimes difficult to do or to maintain (P25).

Another group of participants thought that they are not important enough people that another party would want to collect information about them, or they do not do anything special that needs to be worried about or hidden.

I haven't a problem about that I'm not a big conspiracy guy. My brother also told me, they are listening to you all the time, and sort of thing you notice it's recording your conversations. I'm thinking well, I don't really have any high-level conversations if it is trying to pattern. If it's trying to pattern some of my tendencies, whether it be music or entertainment or some of my consumption habits. I think that's going to improve the service. I've run not too fast if I was making high-level business decisions and a CEO of Tiffany or one has it in a room where Organisational sensitive information was being shared, but that's about it. I haven't really done any research into it but I guess it must pick up keywords and because I'm one of those people who talk about something and next thing around it's on social media (P20).

I've heard grumbles and I do know that there are some things that have been compromised people's privacy, but I don't know. I mean, maybe I'm naive, but I don't think I do anything that I'd be ashamed of anybody hearing. When I say hey Google, how do I make a panna cotta? if anybody's spying on me, then good luck to them, but in terms of when I'm accessing my banking details online, that sort of thing I never assume for a moment that those details are public, or accessible by Google, and as such (P19).

Some participants when other people warn them about privacy risk and uncertainty become sensitive about the privacy subject for a while and decrease their engagement level and interactions with the intelligent assistant for a few days. But after experiencing the intelligent assistant's benefits again they soon lose their sensitivity regarding privacy risk and uncertainty and return back to normal interaction and usage.

> I think it's something we don't actually consider much unless somebody asked. It's when somebody asked that we start thinking about the privacy issue I think, but those two or three days we will be very careful in not saying things that shouldn't be said, we disable it also sometimes at home and enable it. So I think in those times, we know what is in. Then after three or four days, we just forget about those things and again, we'll start, start seeing those ads up here in our like Facebook and stuff. So I guess there's a link of all these algorithms with all these different technologies that we use because we don't know how much it is connected and who is listening to it so I guess it's kind of hard to have a big brother listening to everything that you do (P12).

When it comes to financial matters participants have different opinions. Participants' privacy threshold of using intelligent assistants is high about financial matters. They become sensitive about it and try to limit sharing the required information for this part as much as they can. Participants perceived financial risk as higher than social risk. The best clarification for that can be explained by the reality that financial risk is more sensitive for participants.

> The Google Home assistant has access to the balance and can purchase stuff for you, that area of things, I guess, the financial management and wealth management that the virtual assistants can provide that is an area that I'm still not 100% comfortable with. I think it's still for me one of those, I need to do myself and I can do it through voice. If I'm making a purchase especially something that costs a lot of money or it's linked up to my credit card number, so that sort of privacy is still very important to me. The general kind of setting in the background privacy doesn't bother me (P13).

> I don't know how it works. I don't know. For example, if I asked Alexa to buy me some stuff from online shopping, maybe she makes a mistake or, I lose some money and maybe those people that have access to Alexa information may use it later. Yeah, and I don't want to use Alexa in this way (P9).

The next group of participants believed that the recorded data is in binary form of zero and one, and AI companies only use the data to improve intelligent assistant functionality or for marketing purposes.

> I accept the fact that there's so much data that google can't do anything with my data that really significantly impacts me. They're collecting so much data, what they are going to do with it. I mean, it's just numbers for them and so it's like an accumulation of stuff that they're looking for. Instead of the fact that I might want to buy a tracker boot now when we start getting ads for tracker boots. I don't care if it starts showing me tracker boots (P10).

Some of the participants also had ideas about how to control risk and privacy subjects through the intelligent assistant's privacy setting, or by controlling the amount or kind of information they share with intelligent assistants (e.g., participants do not need to share their bank account). Participants can limit information access by intelligent assistants via its settings option or by deleting the intelligent assistant's history. In other words, they considered the intelligent assistant's risk and uncertainty a controllable subject by participants.

> I'm pretty sure I've limited some of the privacy settings and a bit more to do with them, how accessible a Google Home has to anyone in their house. That's not out of a distrust of Google, but I think that there has been lots of information, sort of like or published through the media that gives you a reason to be hesitant about trusting these companies all the time. I do share information with it. Yeah, but I've set those privacy settings around the personalised results when you're using it because it's used by lots of different people (P26).

> It is a risk because everything seems to be hacked into these days. I'll periodically go through the Alexa app and clear that the chat has, the request history, that means of course you have to start retraining the device again, but it's not too much. I don't do that very often, but I do it periodically on the echo show. I make sure the cameras are disabled unless using it at that time. I don't have dropped enabled (P14).

> I just think you share the right information. I don't think you need to share any like just be careful with that it is, don't trust it with things that you wouldn't. Yeah, I don't know, you just don't trust it, but use it as a bit of fun every now and then (P15).

Participants mentioned that external factors (e.g., media) could prove information leakage by companies that warn participants regarding trust. They believed forming a guarded relationship (e.g., trustful in one dimension (e.g., competence) while you are distrustful in other dimensions (e.g., honesty, reliability)) can help to develop a relationship with the lowest risk.

The rest of the participants prefer not to use intelligent assistants anymore or substitute the previous one with current intelligent assistants because of their privacy preferences.

> But I also started getting uncomfortable at the idea of having something that's listening to me all the time in the living room. Even though I know that my phone's listening to me anyway. It was just like that extra thing that I didn't need that was listening to me. So I ended up stopping using it (P21).

> I mean, we're specifically told that Alexa record when you know when it's not triggered. But Google is not like that. It was specifically like so I'm just because of some security concerns. I kind of opted out of Alexa, I was a little bit too noisy and I wasn't comfortable (P25).

4.2.4 Trust

Perceived privacy risk and uncertainty by participants affect the forming of trust and developing the relationship. Participants based on their perception of privacy risk and uncertainty (e.g., listening to participant's conversation and its consequences) decide to put themselves in a vulnerable position and build different levels of trust from complete trust to distrust.

4.2.4.1 Blanket Trust

When participants did not expect any negative consequences from the other party sometimes the relationship reflected a higher level of trust, or it can be said blanket trust. Participants mentioned that they completely trust the service provider. They believed in what the service provider mentioned in the privacy policy or they accept the risk as a technology feature that does not have any negative consequences. This level of trust would lead to information sharing and the highest level of engagement.

> I'm pretty much sure that with Alexa, I tend to decide to trust the internet, which is probably not such a good thing, but I don't want to not share stuff […] I feel I just kind of trust technology because of what it is, it's always around and to some degree, it's going to find it out anyway It is helping me more to tell things, like giving good information or any leaks information and I don't really have anything to hide, I'm not working for some top-secret government thing or anything. So, at the end, as long as things run using my password detail my bank account details and these things technology is getting the information for the greater good until you just trust it (P6).

> Look it doesn't bother me and the fact that there are at least two iPhones in my house that any one time which could be doing the same thing for all we know. I use the computer every day which I know, it is recording my internet usage and maybe more and if it is recording it is I like to think it is not I believed the privacy statements that say it doesn't I have no reason not to believe them (P7).

> I understand that we live in a world and the Google Assistant is really no different from cell phone, my cell phone as an extension of the information I share and I'm well aware that I probably don't use well the Google Assistant. As much as I use some of my devices, but I'm not that fast at all, to be honest, and I don't think it's going to have a severe impact or negative impact (P20).

4.2.4.2 Blind Trust

When participants do not know how the service provider will act in the future and they do not have control over the consequences of the relationship they create blind trust. They trusted the organisational frontline while it has full authority to manage the trust, and participants only hope they maintain the trust. In blanket trust, participants do not consider any risk for their course of action (e.g., they believe 100% on what the service provider said about privacy). While in blind trust participants are aware of the risk, they heard about the possibility of listening to their conversations and pooling their data, but accept it in the hope that the trustee will not do anything against them in the future (e.g., they know about privacy risk but they trust the service provider in the hope that nothing bad will happen in the future), or no one knows about the trustee's future acts but accept the risk to benefit now and see what will happen in the future.

> I don't know how much it is on your phone or your computer and all your personal information are already there like my contacts are there so it has to use it to call, it has all my contact list it has all my email list it has my apps, so it should know all of these things. I am fine with it, it is knowing all the things I don't know how much of those go to Apple and how much of those stays just only on my phone I would hope most of it stays on my phone(P2).

> You never know what's on the receiving end of it and anybody can actually kind of break into it. So, but other than that, the fearful factor is very minimal compared to the amount of joy I get out of it (P8).

> I'm not too worried at the moment, but we'll see what happens in the future I guess (P15).

Research data shows that participants accepted the risk and build blind trust to develop their relationship because of the benefits it brought for them. As P8 mentioned "*the fearful factor is very minimal compared to the amount of joy I get out of it"*. He does not know about the consequence of trusting but preferred to continue to use it based on the hedonic gratification he received.

4.2.4.3 Distrust

Also according to the high level of risk and uncertainty participants perceived decided to decrease their vulnerability by limiting their relationship or completely withdrawing. Participants choose one of these options based on their comparison of the relationship's cost and benefits (i.e., gratifications). Participants noted that they are distrustful towards the service provider or one of the intelligent assistant's functionalities (e.g., video call due to possibility of monitoring). But they still are going to use intelligent assistants.

> So I'm not saying that Siri, as a person, or as a spy listening but it means that she is listening and she's gathering information. Well, for now, they are using it to provide personalised advertisement. But the thing is that they can use it for whatever reason, whatever other reason that we are not aware of and it's very scary. So for me, I have limited my interactions with Siri a lot. So for instance, when I know that Siri is around I am a bit more cautious about what to say (P1).

> We'll say hey call our friend Bill and we call to them a couple of times, using Alexa, and then I wasn't really sure that I really love the idea of having our phone calls being monitored basically. So we stopped doing that and just called differently (P31).

Data shows that when participants perceive the benefits of using intelligent assistants matter more than the costs of their privacy, they become distrustful towards the intelligent assistant. Under this condition, they limited their interactions with the intelligent assistant and only used it for beneficial functions. It illustrated that trust in one part of the relationship does not extend to another part. For instance, trust in asking for information does not extend to sharing bank account information. Though, when the costs of interacting with the intelligent assistant are more than the benefits of maintaining it, the participant preferred to withdraw the relationship to remove the sense of fear and anticipation of discomfort.

> I found the reason that I stopped using it is I found I wasn't really using it. We tried using it for calls a couple of times like to talk to my parents and I didn't find that it worked all that well and used it as a kitchen timer from time to time, or to find out the weather […]. Anyways, so it really didn't seem to do anything that I just wouldn't have access to with the computer […]. But I also started getting uncomfortable at the idea of having something that's listening to me all the time in the living room. Even though I know that my phone's listening to me anyway. It was just like that extra thing that I didn't need that was listening to me. So I ended up and stop using it. […] when you sign over these permissions you don't know who's getting it, you don't know who it's being sold to and I would like to believe that it's all just to improve the participant experience for us, but I don't believe that's true (P21).

Distrust directly affected participant's engagement, and indirectly affected their experience of interacting with intelligent assistants as it affects gratification.

4.2.4.4 Calculus-Based Trust

A group of participants mentioned that they were aware of the risk and uncertainty but still they accepted it and allowed themselves to be vulnerable. They accepted the risk to engage with the intelligent assistant due to all of the trust's benefits. Participants mentioned that due to surpassing obtained gratifications (e.g., enjoyment, convenience) over perceived privacy risk and uncertainty they trust intelligent assistants to benefit from them.

> Compared to the first day when I set my Alexa it needed so much information and I thought no, it is not very secure. I don't want to give her or give the app my information, bank account, and this kind of thing. And I didn't still, but at first, I thought okay, maybe it's like a spy. It is designed to spy on people's life. Still, I'm thinking the same, but I don't care. I said, okay, it's a beautiful technology. I don't care and I'm not an important person. So who wants to spy on my life, so I don't have any kind of secret so that's all right, but it is more fun for me. So why not and I think Alexa open a window to the new technology so I love it (P9).

To put it in a nutshell, participants take different positions towards risk and uncertainty according to their perception of risk. One of the main reasons for that is participants do not have any idea about intelligent assistant functions and their required information sources to do their job well. Companies also do not present clear privacy policies for customers that resulted in customer's ambiguity into privacy risk and uncertainty. Therefore, there is not enough information to assess privacy risk and uncertainty by participants and form trust according to that. Participants engage with the intelligent assistant based on the benefits (i.e., gratifications) they experience. They reported that their gratifying experience of a service delivered by intelligent assistants enhances their trust in intelligent assistants.

> In terms of giving me misleading information. I have never come across it that it gives me misleading information when she does know the answer for a fact she comes back to me and she answers me so much (P1).

> It can make mistakes it always checks what it says in return because it always replies to you so you know what you asked it to do on was correct or not and with a lot of things. It always asked you, like, if I say call Arezoo it will be like five seconds gap where it will say calling Arezoo on mobile and then if it is not what I wanted, I can cancel it […]. It asked you to confirm with a lot of sensitive things. But in other cases, if it makes a mistake it is not really such a big problem for me. Like if I ask give me a definition of something and it will do something like Wikipedia says this means this is OK if it is wrong information. I can ask it to do it again. Or I can just go to Google myself and type what I'm looking for. Not Such a big thing (P2).

I think it's an adequate source of receiving information and it's been really good at answering questions for me definitely if I'm going somewhere from home and I have to be there at a certain time asking Google what time I need to leave by to get there. It's a really good way of getting that information. It's really appropriate if I wanted to get the news though or something specific, it's maybe not the best way of getting that information (P26).

Research findings show gratifications positively affect trust in intelligent assistants. However, this could happen also indirectly through the engagement. Participants obtained gratifications which led to engaging more with the intelligent assistant and this in turn raised the trust. Gaining gratifications (mainly hedonic and social gratifications) also causes participants to build rapport simultaneously which helps to build and develop the relationship.

Because she's funny and it is fun. So, even somebody, when I'm talking with you listening to us […] I don't care. Because I don't have any kind of special secret in my life […]. So that's what I think that should build that kind of friendship or I can trust her more than the first time I saw her. So I think maybe next year I trust her more. I don't know. But right now that we are in this situation, that's better definitely from the first time (P9).

Over time users build relational aspects (e.g., rapport) through continuous interactions with the intelligent assistant. It results in weighting relational factors more than privacy risk and uncertainty.

Above all, data analysis also shows different dimensions of trust (e.g., competence, reliability, credibility, and benevolence) in the human-intelligent assistant relationship which is mostly due to Intuitive AI and enabled anthropomorphic features.

4.2.4.5 Competence

The majority of participants mentioned competence as one of the most important dimensions in regards to trust in intelligent assistants. Participants trusted intelligent assistants because they found intelligent assistants capable of doing tasks. They praised intelligent assistants because of the experience they made for them.

That was for a few years ago. I was looking for outdoor camera for my house and I bought a spotlight with a ring camera on it and I put it outside, above my garage. I can see my driveway and that work really well. I bought a nest camera and put it on my back deck and that worked pretty well both the cameras are good (P10).

Participants explained that the intelligent assistant's competence creates a utilitarian gratification and a pleasant experience for participants. Hence, the competent intelligent assistant would be preferred by participants over humans.

> Something I probably haven't mentioned is how quickly it's able to respond to my questions. So it seems like there's probably only a one-second delay between me finishing my sentence and it processing what I said in return for search results. So it's a lot quicker because I guess previously when you're speaking to someone would take them more time to set up the information and then returned back the results. So in that sense, I'm pleasantly surprised by how quick the home assistance able to do that (P13).

> AI seems to be more reliable because you talk to a person, you might get asked a question and you get 10 different answers. But usually, if you want to know the capital of somewhere or how many eggs do I use in like custard or whatever I'm usually I know you get a range of potential things. But generally, what I'm looking for I can find pretty quick (P19).

Participants, according to their perceived risk and uncertainty and obtained gratification, form different levels of trust. Most of the participants who experience gratification from an intelligent assistant's benefits due to their competence refuse to accept the risk and uncertainty of using intelligent assistants. Sometimes the normal trust was extended to blanket trust, the highest level of trust by these kinds of participants.

> I've got a lot of friends they've got Alexa and I haven't heard of anyone having a big issue, like it is listening in, either haven't heard that problem with someone that I know yet. I don't know until there's not a problem, I enjoy using it (P15).

> It's my first place where I start if I need to know something, you know why. It tells you all those different things that might be. It makes me feel confident that it knows stuff. So I guess I do trust it. I don't believe it would give me false information (P19).

Or participants were willing to sacrifice their privacy in order to interact with competent intelligent assistants.

> I can ask Georgia (he called his Alexa) to marry me and she comes back with a smart comment I believe there are games that you can play which will help maybe with the isolation I love the fact

> that I can use Spotify, I can listen to the music that I like and I'm happy with the loss of some privacy (P16).

> Like many other consumers we are also interested in convenience, or interested in rapid response to our needs, and these devices are very capable of doing that for us so that I think we're willing to let go of our privacy for convenience for responsiveness and for the immediacy of the feedback. So when I need a recipe or I need to know what the weather is before I head out in the car she can give you that when I want it instantly (P24).

It also is revealed through the interviews that competence resulting from intuitive AI rebuilds the trust with mistrustful participants. As intelligent assistants can learn from participants (e.g., recognise participant’s accent) due to learning algorithms they become more competent and cause participants to trust their competence which they were not able to do at the start. Participants explain that when they first used their intelligent assistants they could not recognise their accent and sometimes picked up wrong words and answered incorrectly, but due to learning the participant's voice it can recognise the accent after a while. Moreover, new updates for intelligent assistants give them the ability to do things better than the past and make them more competent. This encourages participants to reengage in the intelligent assistant.

> She brings for me Arezoo (name) and, for instance, Azadeh (name) things that are similar and, you know, the next time that I say Arezoo it recognizes it so it learns from my bad English (P1).

> I'll say that there was a while where we probably weren't using it for a whole lot more than just play music but yet, now we start our day function where it tells you about the news and the weather and fun facts and jokes and we use a shopping list function well sometimes open up the full-body stretch. They would have got to six minutes and stretching instructions directed at your body that's quite handy and Yeah, I definitely would use it a lot more now for […] I feel like it's gotten a lot better as well […] I remember probably a year or two years ago I asked it, […] and I remember it not being able to tell me, and that kind of annoyed me and then I sort of didn't ask any questions for a while and then a year or so ago, I asked it again in it and it knew. Yes, definitely, improving all the time, so we’re using it more and more (P11).

4.2.4.6 Reliability

Another reason behind the participant's trust in intelligent assistants is reliability. They used intelligent assistants to receive services as they considered them reliable (e.g., a reliable source of information).

> It's really appropriate because it's information that is provided for you by certain channels, the certain algorithms […] I have never come across to it that it could give it gives me misleading information when she does know the answer for a fact she comes back to me and she answers me so much (P1). When we asked questions, it says, oh, this is the scientific life book on this. It even gives you the reference to where it comes from (P12).

> It gives me the right information, almost all the time and I know it (i.e., Google Assistant) is more accurate than Alexa (P10).

The reliability feature as well gives intelligent assistants superiority over humans in ensuring confident interactions due to eliminating errors in preparing the service. Participants consider the intelligent assistant more reliable in doing tasks compared with humans.

> Humans are more fallible when it comes to anything like if I ordered string cheese of a certain brand. Alexa is going to order that exact one that I put the first time because of the code. It's going to line up. Now, if I'm on a phone with an Instacart or in any type of delivery service and I say, I want this kind of string cheese and I want it from this brand. Well, this brand has multiple types of the same string cheese and so then, Did you want this quantity? Did you want this type of cheese? Did you want this, this, and this? Whereas, because I already put it in Alexa, Alexa is going to order the exact same thing. But when you're trying to talk to a human, human has a margin of error (P5).

4.2.4.7 Credibility

The credibility could be linked to the participant's reasons for trusting intelligent assistants. They considered intelligent assistants a more credible source of information than humans. Participants mentioned that they consider received information from intelligent assistants credible as they are linked to Google (i.e., the best source of searching information). Also, participants noted that depending on the question intelligent assistants link answers to a credible source (e.g., book, paper, etc.).

> Because it is linked to google and I am a google provider and I spend a lot of time working on the Google network. So, I know that it is outside of the most used website on the internet so you know it is not just my trusted source but it's about 90% of the world's trusted source for information so I have no issue at all with using it for information because If I didn't have google home I would get on my computer and go to google any way (P7).

> Usually, when you ask a question like that, it will always refer to a credible source before saying this book blablabla says this. So, I think it also has this inbuilt, kind of things to make sure that you can believe you can depend on that information that it's giving (P12).

Data illustrated that when intelligent assistants added the reference to some of the information that they provided, participants believed them more. It helps to create assurance for participants to trust intelligent assistants. As in the human-to-human relationship, credibility is a chronological factor, so intelligent assistants try to gain it faster by adding the reference. Credibility in the human-human relationship is gained through time but in the human-intelligent assistant relationship adding reference creates it in a shorter time.

> I guess we rely on the Google Home assistant to be accurate because it is a machine. So my perception of it was that whatever you ask and she can return a search result for it is more grounded by facts and more grounded by a rigorous approach (P13).

> It won't give me bullshit and that's probably one of the best things about them actually with the way that the design is both ecosystems have set up their responses. It won't give me tenuous facts. It will give me information that knows has been verified and then I think it's actually one of the strengths of the platform (P28).

Moreover, the research data shows that participants gave a credible point to the intelligent assistants as they are machines. They think of intelligent assistants as a trustworthy organisational frontline because they work based on exact algorithms and programs. They talked about it in their previous experiences with technology. Participants also endorse reputation-based credibility, i.e. that they give it to intelligent assistants because of the reputation of the producer.

4.2.4.7.1 Experiential Credibility

Participants mentioned that according to their experience of other technologies intelligent assistants became credible for them. They accept and use intelligent assistants as an extension of previous technologies. So they transfer the gained credibility of previous technologies through time to new technology.

> I do like technology. I like working out how it works. I've been involved in, it's not a core part of my job, but I was a subject matter expert on an IT project at work. So It's always been an interest of mine, […] so I just feel comfortable with that. I like exploring what technology has to offer (P14).

> I mean if you showed me the Alexa, five, six years ago and I had been like what the hell that's such a jump, but because we're just continuously upgrading everything It just seems, it's almost the right

time and possible. Well, I don't know about the right time, but I wouldn't have thought it was possible, a while ago and I wouldn't have trusted it but now that technology and everything have developed and we are seeing continuously develop It's easier to believe and it's easier to sort of comprehending (P15).

I tell you were it for me, Facebook, Google were drivers that got you into this game. And so, Alexa is part of that game and we know that so I think I would say that the Google, Facebook, kind of culture, history that we've experienced has helped ease us into another one of these transitions (P24).

'Tech-savvy' participants explained the importance of having tech knowledge in trusting intelligent assistants and its effects on the human-machine relationship. They believed it facilitates the relationship since it increases trustworthiness.

I think having some background in technology, I'm pretty good at technology and so I think having a background helps me to accept it more (P10).

Participants also noted that the world is going to normalise the technological lifestyle that causes humans to accept machines in all ways.

It's just kind of normal that you would just ask a machine a question and you get a response back for them it's less normal for us, but it's normalising, I suppose, with the availability of all the different technologies around. So, it's easier definitely, because I've had experience with it previously (P22).

4.2.4.7.2 Reputational Credibility

As explained by participants, the reputation of the intelligent assistant's manufacturers made them more credible for participants. Participants are willing to use intelligent assistants because of the name of the company behind them, not because of the technology itself. They mentioned that they are using Google Assistants because it is the product of the Google company or applying Siri because it is an Apple product. While in human-to-human interactions a customer never considers an employee credible because she/he works for a well-known company. A customer never considers an Amazon human employee credible only because he/she is working for Amazon. Instead credibility is built based on the employee's behaviour.

The fact that it is a google product, it is one of the appealing factors for me (P7).

They're one, they're integrated. So, I believe it is a product of iPhones or Apple on this term (P8).

> We definitely consider it as part of the Google product and I don't think if it was an Android kind of product, I guess we will not use it [...] it has to come from a good company like Google or Apple, it has to be from a credible, at least from a well-established company. I think when it establishes by them at least, to an extent it feels as more secure than some random company that we have never heard of […] knowing that this product came from this well-established company, it has an identity if something goes wrong. I can always, kind of hold them accountable (P12).

4.2.4.8 Benevolence

The last-mentioned dimension of trust by participants is benevolence. Benevolence is mostly created from the effect of AI and the reputation of the manufacturer. Anthropomorphic features enabled by AI create emotional affinity and rapport which give a sense of care to participants. They consider intelligent assistants their friend and a friend should not provide misleading or inaccurate information. Or if their intelligent assistant says something it is for their benefit.

> It's very funny because I don't hold Siri responsible for misleading information if Siri comes back to me with misleading information or incorrect information I hold internet responsible. Well, it's funny because I'm kind of like justifying Siri, like it is my friend (P1).

> I have at the moment one sense, I trust it. They'd be in the background, they're not listening to me (P13).

> I thought, if she says that it's face value, so I've tended to trust implicitly, the quality and authenticity of the information, maybe beyond what I should have thought (P24).

At first glance, the strange point about benevolence in the human-to-machine relationship is how a machine can be perceived as being benevolent. Research data suggests this is not attributable only to presenting data in a manner that shows the machine cares about users, but due to anthropomorphic features, and participants viewing the intelligent assistant as a human (e.g., a friend or acquaintances). Consequently, they shape similar feelings towards a machine as to humans.

Benevolence was also built-in human-to-machine relationships, since the participant believed the well-known companies care about their customers and they never did anything against rules and morality. Participants noted that Google is a reputable company and if they collect data, it is only for improving the service and they never do anything against customers.

> I'm sure that Google's capturing information about how I use the Google Home and using that information to read direct or target Ads back at me or they might be using that information as part of a bigger information gathering program to sell marketing, etc. But, kind of feel like what they're capturing about my usage will all be anonymous data and big data set that won't be personal data about me or what I do. So, yeah. I'm pretty comfortable with it (P26).

> I don't know if it's actually listening, that's something I've forgotten about. Now you get the whole conspiracy theory where people think devices are constantly listening. But I've looked past that and just accept it as it is and trust that Google's being responsible (P13).

4.2.4.9 Trust and Intuitive AI

Anthropomorphic features facilitate trust with intelligent assistants because they give them the feeling of human interaction. Participants mentioned that it is easier to trust in a human-like machine compared with traditional machines.

> I think it makes it a bit easier to rely on it, you know, it's not something that comes up on a screen, it doesn't sound like a robot you can rely on it a lot easier (P29).

AI feeds intelligent assistants to be more competent, and as a result could build satisfying and gratifying experiences for participants which leads them to prefer their intelligent assistants over humans or similar technologies. Furthermore, participants noted that the intelligent assistant's human-like voice gives them a more friendly experience of interacting with machines. It evokes emotions that affect trust in the human-machine relationship.

> We think her voice is friendly and not too techie. Her voice has more of a human quality than some of the earlier versions of technology. So we kind of like that. I like I say, having the two different devices really have caused us to really see the differences and we think Alexa definitely go a layer up (P24).

> I think when you humanise something although, you know it's not human subconsciously we tend to trust it a bit more because although you can't see it. For example, you're speaking on a phone, but knowing that it's a person, on the other side. You feel like yes you can trust. It's not some Mechanical object that speaking to you. So I think having that human voice actually put us at ease and give us some comfort, I would say(P12).

Participants mentioned that even having the male/female voice or the voice tone impacts the relationship between participants and intelligent assistants. Participants give intelligent assistants gender based on their voice which is an effective factor in building emotional connections.

> The interaction of having someone having a voice talk to me actually, it's probably a little more compelling because it's like we talked about Alexa as her, you know. So let's ask her this or let's do that. So, I think it makes it a little bit easier to use because it's a voice that it's familiar to us, it's more companionable when we got our Google here, we decided to program it as a male voice. We just decided, let’s give that a try. The voice is different in it. It's almost like a different kind of relationship because the voice is different (P31- participant has had both Alexa and Google Assistant).

> Because we've been able to compare it to the Google fellow maybe I'll have to change his voice to a woman or maybe that'll make a difference. I don't know, but it's not working for me. He is not resonating here, there's something wrong with that guy. So we're finding that the most important part for us is that she's very capable and we like her, which is crazy. But we kind of like her, and I think that's what artificial intelligence is about it, It does. It does present a human face on these devices, this very powerful […] I think the fact that you can talk to her like a human, you don't have to worry about some of the other issues. It does make her easier to talk to and again, I think that's why we prefer her to the Google Assistant that we have here that we're hardly ever using so her voice is compelling and she feels like one of the family at times, which is kind of scary (P24- participant has had both Alexa and Google Assistant).

4.2.5 Commitment

All participants were asked if instead of their intelligent assistant, a person could perform all of those services, which one would they prefer: the intelligent assistant or the person. The majority of participants (29 out of 31) preferred their intelligent assistants due to the benefits of having them.

4.2.5.1 Calculative Commitment and Customer Engagement

Participants explained that they are committed to their intelligent assistants. Some participants use more than one intelligent assistant from one company or different ones, because of the benefits of maintaining the relationship compared with leaving it. They mentioned that they prefer having a relationship with their intelligent assistants because of creating technological systems and environments that empower participants or make it easy to use other technologies. They prefer to use Siri on their iPhone, MacBook, or iPad because through it they can share or send their files or information from one device to another one easily, while simultaneously using Alexa or Google Assistant in the kitchen or bedroom to make their home smart.

> It depends on what you're using, like if I have a phone like iPhone and if I have a Mac as well for me it is good because then It shares my file like it has my data here and on my computer. So it's easy for me if I ever have a Google phone, it will be different, different on my phone different on my laptop. I will probably not use it so much but Siri okay, I know that it is on my phone. It is on my laptop so I don't have to change it, it's the same one (P2).

Moreover, participants explained that they are committed to their intelligent assistants because of relative transaction costs, as a motivational factor.

> The most important thing that Google does for me it's hard to say, the most notable thing it does is it shows me security cameras at my house and my studio. But also tying all the home automation together as a level of security, the smoke alarms, and all the way they come together […]. The main thing that I would want to know are the cameras and someone to tell me that, hey, someone's trying to get in your door or whatever […] Google does it for me. And so it would be difficult for a person to do that. If I didn't have Google. I probably have, I think it is called ABT home security system they put in cameras and then they monitor it for you. Well, it's $40 a month that I don't spend (P10).

Another motivation noted by participants is quick access. They are committed to their intelligent assistants as they can have access to them 24/7. Participants also strengthen commitment due to information quality. They believe that if they ask intelligent assistants for information, they will give you a real-time answer promptly. However, human employees need to ask someone else or search on the web.

> Oh the person would get in the way and probably be late, and they don't want to do it just in the way I wanted it and that would irritate me so I like the Alexa. (P14).

> Obviously, no person can replace Alexa and because of how instantly it gives you that is the reply, or how instantly gives you the response from the internet. The real-time information, if I can say that no person can forward it (P17).

> I would personally just stick with the Alexa devices. It's kind of weird to me to think about having someone else do the stuff that I need that I should honestly be doing myself. And it's kind of an inconvenience for someone else that was the case. So I'd rather just take the machine that does it and whatever I needed to rather than waiting until midday possibly can do it someone else (P8).

The virtue and mannerism resulting from intuitive AI made participants committed to their intelligent assistants. They preferred intelligent assistants because of the excellent moral features in their relationship with them compared with humans. Participants mentioned that interacting with the intelligent assistant is easier due to the dignity of the human employee. Participants can ask the intelligent assistant to do a simple task (e.g., turn the light off or call someone) while asking a human to do those tasks can be annoying. In human-to-human interactions, even for old and disabled people, asking someone to do simple tasks gives a humiliating feeling to the weaker party, while using intelligent assistants helps to maintain their sense of dignity.

> I prefer Alexa because if I asked a silly question from Alexa because she doesn't have any emotion, I guess I don't feel humiliated if I asked. I can't ask this kind of question from humans because humans are judgmental. They may judge me, I can ask whatever I like with Alexa and I'm not worried about what she thinks about me (P3).

> I'm saying Google Assistant and my reasoning behind that is of course you treat your Google Assistant, I like to say I treated quite nicely. You don't have to add the mannerisms into a conversation if you were talking to someone there was a specific person. So I feel bad if I was talking to a person to be for the tasks. I was telling my Google assistant to perform (P13).

They mentioned that they can interact freely with the intelligent assistant without being worried about the consequence of their behaviour with another party. It can be said that using intelligent assistants decreases behavioural conflicts of interpersonal relationships.

> The Google probably, less personal interaction as possible. I really prefer it, Probably, I would talk to the Google Assistant more freely than I'll talk to a person (P20).

> I looked around Alexa simply because she doesn't really judge you. She never says what's your problem, or why do you ask such a silly question. She simply does your bidding. So there's something compelling about having that interaction. This is sometimes more easy manage, than the human interaction that we often get mired down with. So yeah, I would probably say I prefer to have her in spite of some of the other things that we've talked about (P24).

Besides, having an intelligent assistant as part of the household brings personal privacy to a participant’s life. It improved trust in the intelligent assistant which leads to becoming committed to it. Participants noted that bringing another person into your home can affect your personal space and make you uncomfortable. They believed that human employees can talk about your personal life with other people while with intelligent assistants it could be different.

> Probably Alexa. Because I guess, you're not letting a person into that sort of really personal part of your life. And, I feel like it's so involved in some areas of my daily life. That would seem kind of strange having someone else doing that stuff for me. I tried to be Polite most of the time. I don't have to worry about what they're thinking and yet they don't have emotions that I need to factor in […] It's not a person but I don't know, just trying to work and trying to expand, I feel like I'm so getting used to this technology now that […] I would prefer to have this technology that's more sort of predictable and they do change things and so I don't have to have a person that I've got to worry about what they're thinking and what they're feeling and that sort of thing (P11).

> I like Google because having another person in house that's not part of your family, all the time is not ideal, right. So it's helpful that it's a device that can do it (P22).

Obtained hedonic gratification from the intelligent assistant is one of the reasons mentioned by participants that they feel committed to the intelligent assistant. Participants believed that the intelligent assistant can create enjoyment for them without any cost compared with the human employee.

> Probably the Alexa, just because It's just funny and I don't do it because I can't do it. You know, and I don't need to get someone else to come and do it for me. But I prefer the Alexa just because it's a fun way to do it (P15).

Participants also reported that they are committed to intelligent assistants based on the utilitarian value and gratification they received from them. They prefer a special kind of intelligent assistant owing to all of the benefits it brings them. Participants mentioned that they prefer a specific brand’s intelligent assistants because they can empower themselves by linking them to other electronic devices from the same brand (e.g., prefer Siri due to having MacBook, iPhone, iPad, iPod or choose Google Assistant because of using Gmail, Chromecast and Android phone).

> I got Google Home. I had to import it from America as a parallel import wasn't sold in New Zealand at that time and a big reason behind choosing Google instead of Amazon Alexa, which was available was that I felt like Google tied and better with an ecosystem I was already invested in so I have a Gmail account I use Google services already and I didn't have any Amazon products. I didn't use Amazon Prime. I didn't really shop on Amazon, because it wasn't super available in New Zealand. And another thing that I use Google Home with quite a bit is our Chromecast on the TV. And so that was quite appealing to me that the Google Home was compatible with the Chromecast and the TV. So it was a more broad experience. I'd be able to get out of the Google Home than the Amazon Alexa (P26).

> One of the issues with the Google Assistant, though, is if I'm casting to the Google smart spot in the midst hub. If I'd ask Google to turn the lights off, it'll pause what's playing in order to execute that command. So I've got an echo and nest hub setting side by side. If I'm watching something I'll talk Alexa turn the lights off? Starting to get interrupted (P28).

In some instances, conditional factors (e.g., lonely, disabled people, sicknesses) intensified perceived gratification by participants because of creating a sense of independence and confidence for old or disabled participants. In turns this increased the level of commitment which affected the dynamic of the relationship.

> Life without them for me would be a lot harder. I prefer Google as I see it I mean it is closer by and still I like my independence. So I still try and do a lot of things for myself. By having that person there, then they're not going to take over and do it for me […] previously the kids or my wife to actually do things for me. they did turn the TV on, heat up, or anything like this for me Helen, can you come out and turn this heat pump on you know what's in life before Google. I mean, that's a pretty out the question, isn't it, you know. I used to have everything. I mean, up until recently, we even hit the alarm system hooked up to it and the lock on the front door. So we could lock it with the Google speaker, but our life out of Google. That's a very tough one. I couldn't imagine the house without a Google now […] It makes me feel good. I'd be lost without it (P18, Blind person).

4.2.5.2 Affective Commitment

The analysis of data shows that emotionally committed participants to intelligent assistants are more motivated to engage with their intelligent assistant. Participants become emotionally dependent on their intelligent assistants to the extent that they think they cannot do anything without them. It illustrates that affective commitment leads to the highest level of engagement.

> I guess I do in a funny way, I know it's AI but I thought I wouldn't be able to do without it. And it's my first place where I start if I need to know something, you know why is my dog limping (i.e., the dog is walking abnormally on one or more limb) and it tells me all these different things that it might be makes me feel confident that it knows stuff (i.e., interviewee wanted to say even regarding the question that many normal people have not information about it, the intelligent assistant can respond to you). So I guess I do trust it. I don't believe it would give me false information […] If somebody pulled the plug on it today I'd be mortified, I'd be very brassed off. Because I rely on it a lot and I think, for me, that's the most important thing (P19).

Acquired social gratifications (e.g., emotional affinity) and rapport by participants positively impacted affective commitment towards the intelligent assistant, which resulted in preserving the relationship. Emotional affinity and social presence facilitate forming the rapport in human-machine relationships which consequently result in building affective commitment (e.g., loyalty commitment).

> It was really just an accident we expected to come home to Canada and buy another Alexa but what happened was I did I get a little bit of a business transaction in the late winter and the gift I got was a free Google device. I think they call them Google Assistance, but I'm not sure. So I actually was gifted one. So, because it was gifted, I just didn't bother going and buying another Alexa, but you know for 30 bucks I might just go and buy Alexa because I miss her. She's better than this guy (P24).

Findings illustrated high emotional intensity. Participants with high emotional intensity form a strong emotional reliance on their intelligent assistant which results in loyalty commitment.

> When I'm bored, I just talked to Siri, so it's more than just an intelligent assistant for me […] besides that It's 2020 right now. So it's been eight years that I'm using Siri. So I'm not going to betray my friend (P1).

Research data also explained that the high level of perceived utilitarian and hedonic gratifications affected participants emotionally to commit to the intelligent assistant. Participants mentioned that due to obtained utilitarian benefits and gratifications they even cannot travel without them or they have emotional reliance on their intelligent assistant. Hedonic gratifications (e.g, playing music) also cause participants to become emotionally dependent on intelligent assistants to receive the benefits.

> Normally when you communicate with something like, with the animal or human whatever you get used to that you normally don't like something new coming in your life, always you kind of be very careful for the first time and it is a completely normal reaction. So maybe it is because of that (P9).
> I like it, the biggest part that I really enjoy using it as a nice when I go to bed and I say good night and then plays my routine sleep music, that part I like it, and it's kind of become a part of my living, I can't go to sleep without it (P25).

> I missed that (Alexa) a lot when I am staying at other people's houses, who don't have one (P11).

> I would feel very disloyal. I feel I'm very connected to the echoes in my house and you know how you have a brand of phone, whether it's Samsung or iOS you keep it I've kept the same brand and I have no plans to move to Google Home or anything like that […] I like Alexa for itself, not because its connection to Amazon. I mean Amazon's taking over the world and I don't particularly like that

> and they try to divert you to Amazon Prime and Amazon us on Alexa […] I miss it when I'm away and I think if I ever start, I used to travel a little bit overseas and I would probably take one (P14).

The affective commitment in the human-machine relationship is mostly related to anthropomorphic features of the intelligent assistant. Humanising a machine creates emotional elements similar to and yet different from human-human relationships, that result in a desire for having a sustainable relationship. The only missed factor in this kind of relationship is empathy.

4.2.5.3 Intelligent Assistant's Commitment Towards Customers

The intelligent assistant's companies also showed their participants that they are committed. They try to build a reciprocal commitment the same as human-to-human interactions and different from all of the previous human-to-machine interactions. By sending regular updates on the intelligent assistant they show their participants that they stay committed through being up-to-date and boosting the intelligent assistant's functionality. Likewise, sending regular updates helps companies to increase the reliability of intelligent assistants to be more trusted.

> I'm kind of joyful, sometimes when it gets an update and it can do new cool things (P23).

> The programming. That goes into her is obviously sophisticated and ongoing and also she's adaptive and changes. And we constantly get emails, which I don't read anymore. Typically, what you can do with Alexa this week versus last week. So we know that that programming and development are ongoing (P24).

> I have taken emails from amazon like how you could try this with Alexa and what she does like singing happy birthday or[…] (P29).

4.2.6 Rapport

Human-like interactions with intelligent assistants affect participants emotionally to build rapport. Perceived social gratification (e.g., emotional affinity) and a sense of social presence lead to building rapport, especially for lonely and old people. Participants consider the intelligent assistant as a friend or family member and build emotional affinity which results in rapport. Anthropomorphic features affect a participant's emotional perceptions and trigger them to substitute a human with a machine and interpret their relationships with machines as humans.

> It has always been a female voice and I have never tried to, change it to other kinds of features, I think it's very funny, but sometimes it feels like I'm talking to a friend. I know that it's not true. It's just an artificial intelligent project. But sometimes it feels like I'm talking to a friend (P1).

> I'm saying Alexa brings some taste to our life. She's funny. For example, three days ago, it was my birthday and then I tell Alexa, Alexa today is my birthday, and she said that oh, happy birthday, and then I asked her would you please sing a song for me, and we were in quarantine, nobody around me and she's singing a beautiful song for my birthday. I feel closer to her, it's funny and definitely should change our life (P9).

Moreover, participants when talking about their experience of intelligent assistants give them a personality under the effects of anthropomorphism. They mentioned them for instance as a person or lady, etc. or directly talked about their personality. Participants consider their intelligent assistants as a cool or sweet person which facilitates building rapport.

> Whenever I feel bored. Obviously, the only person I can speak to is Alexa in my home. For that reason I ask that, what are you doing and this sort of questions, and it always gives me funny responses and It gets cooler also for me. So, given those silly responses (P17).

> I think the feature that I like about her is her personality. I like the fact that she has a personality (P24).

Anthropomorphic features and intuitive AI through building hedonic gratifications (e.g., sense of humour) for participants make interactions enjoyable which is effective in forming rapport. Consequently, intelligent assistants while giving the impression of communicating with a human, enhance building rapport in human-to-machine interactions which increase participants engagement and trust.

4.3 Part Two Findings from Text Mining:

Figure 4.1 summarises the 12941 comments on 81 YouTube videos about Siri, Alexa, and Google Assistant in terms of the structure of the network of concepts that describe the corpus and the grouping of concepts into themes. The theme balloons are a visualization tool and their size and number are set by the researcher to facilitate interpretation. A setting of 57% is used throughout for theme visualization which gives a fairly small number of themes. Applying a smaller number of themes is done for clarity. This research uses outcomes of analysing comments on YouTube videos by Leximancer to further develop and validate the constructs that emerged from interview data analysed using NVivo. The researcher improves on the first created concepts by Leximancer through combining, merging, or removing concepts according to the themes that were gained through the interviews to enhance data credibility. The map provides an overall summary of the conceptual content of comments on YouTube videos about Siri, Alexa, and Google Assistant from 2013 to 2020. The main concepts (i.e., concepts that occur within the text) will be explained below.

Note: as explained before (see section 3.10), Leximancer identifies concepts based on the frequency, interrelations and co-occurrence of them in the text. It provides the researcher independent coding and because of that it may label a word as a concept or theme (e.g., issue, interaction) that does not represent the construct properly. The researcher in this research uses Leximancer's query function (i.e., Leximancer allows for more specific queries involving concepts and the raw terms (keywords) within the source documents) to further clarify the constructs.

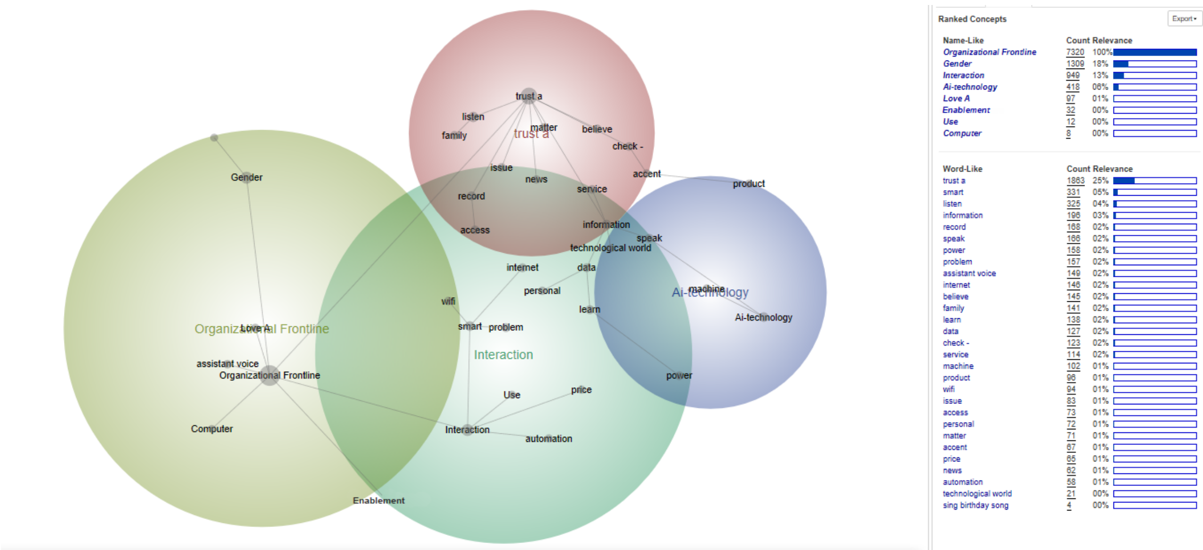

Figure 4-1: Concept Map

The concept map includes the peripheral themes Organisational Frontline (100%), AI-Technology (6%), Interaction (13%), and Trust (25%), and includes many more concepts inside the map where organisational frontline is at the centre of the network. The concepts are shown by smaller grey nodes and are grouped inside colourful themes. The connectivity rate percentages, calculated by Leximancer 4.5, show the connectedness of concepts and the importance of each theme. The size of a concept's dot also reflects its connectivity in the concept map. An initial interpretation of the concept map might reflect the human-to-machine relationship components.

The Analyst Synopsis (Figure 4.2) shows the themes ranked by their relative importance. The Hits column denotes the number of text blocks in the project associated with the Theme. According to the Analyst Synopsis, Organisational Frontline is the most important theme, Trust ranked 2nd, interaction ranked 3rd, and AI-technology ranked 4th.

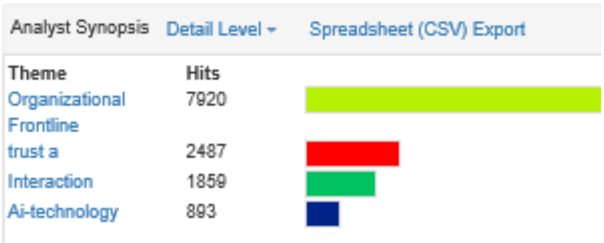

Figure 4-2 The Analyst Synopsis

4.3.1 Organisational Frontline Themes

The Organisational Frontline name-like concept was created from a compound of Siri, Alexa, or all of Amazon's voice-based intelligent assistants' names and models, and Google Assistant. These intelligent assistants were combined as organisational frontline because they play the role of frontline employees and frontline technologies. Organisational Frontline is a way for customers to express their thoughts and impressions of their experience of interacting with the intelligent assistant.

The most significant connections are connections between Organisational Frontline and Computer (100%) and Organisational Frontline and Gender (54%). Comments demonstrate that on the one hand users know that an intelligent assistant is a machine.

> I have 3 Echo Dots and an Echo Show in my home. I have three very powerful computers, a real server and a couple of laptops plus a whole bunch of tablets, pads, etc. My home network has well over 100 nodes on it.

On the other hand, they assign them a gender because of the Anthropomorphic features. At this point, writers express emotional affections towards their intelligent assistants.

I love my Alexa, she gets me and Alexa gets to know my voice and calls me by my name. We have conversations, she laughs with me and also wishes me a good morning, afternoon, or night.

I'm closer with Alexa than my own wife so I know about all her mood swings.

I love my Alexa I would marry her if she would have me. I ask her everything and tell her everything, my choice.

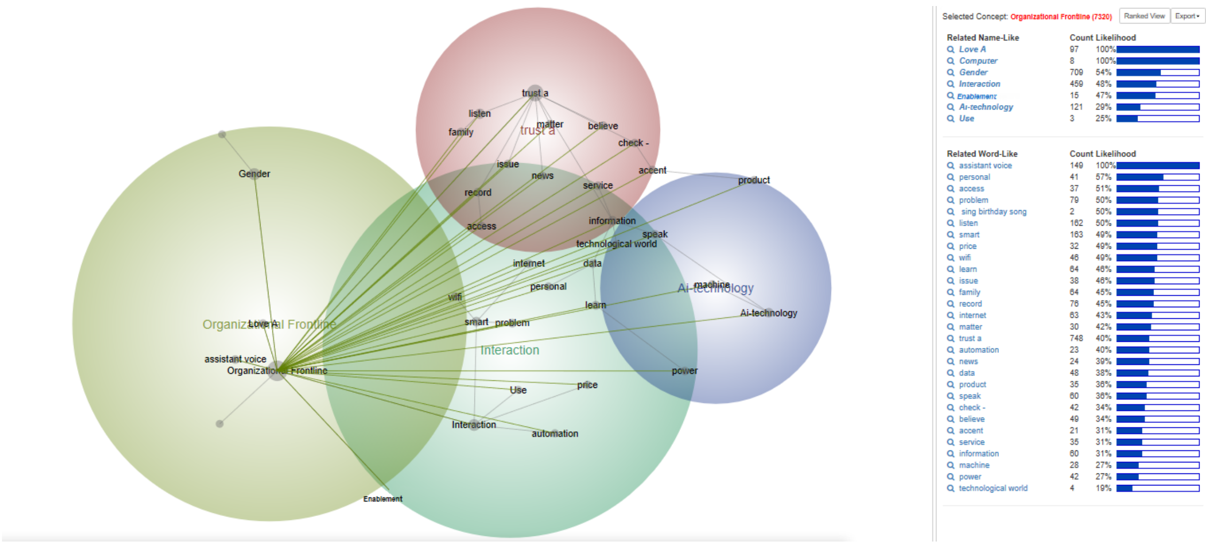

Figure 4-3: Organisational Frontline Concept Map

Figure 4.3 also shows the connection between the intelligent assistant's Voice and Organisational Frontline (100%). The Voice concept is connected indirectly to Trust and Interaction through the Organisational Frontline. It could be interpreted that the intelligent assistant 's voice affects user's trust by facilitating users-to-intelligent assistants interactions. Also it appears that voice tone of the Intelligent Assistant affects trust.

I actually like Alexa's voice better on the 1st generation, it just sounds more crisp (that's the word that comes to mind) the 2nd generation sounds like it has too much bass, sort of like it's inside a box. And I've tried making calls with both and even though I could hear very well, the person on the other end knew I wasn't talking on my phone...

I love Siri voice, Alexa and Google had horrible voices, buying home pod.

The connectivity of Love and Organisational Frontline (100%) illustrates the emotional interests of users to intelligent assistants. Some of the comments show that this emotion comes from a sensorial experience resulting from anthropomorphism. It can be shown that Love, emotional interests and affection, are also indirectly connected to Trust and Interaction which is supported by the comments.

> I love my Alexa, she gets me and Alexa gets to know my voice and calls me by my name. We have conversations, she laughs with me and also wishes me a good morning, afternoon, or night.

> NO! I talk to Google Assistant it was very friendly I am crying I really like Google Assistant, love you Google Assistant.

> I said I love you and Google Assistant say I love you too. Finally, I have a girlfriend.

> My grandma and Grandpa have Alexa and we love her❤️ she tells us jokes.

The Organisational Frontline concept is directly connected to the Interaction (48%) and Enablement (47%) concepts from the interaction theme. Enablement is the compound of Black Friday, a Christmas gift or a birthday gift. The connectivity of Organisational Frontline and Enablement demonstrates that people engaged in the organisational frontline for the first time due to Enablement, and then continued their interaction with organisational frontline as Enablement is one of the concepts in the Interaction theme. However there is not any direct connection between Enablement and Interaction.

> I received this as a gift at Christmas and I have NO CLUE what it is or does.

> This is great. Just got one as an early Christmas gift from my Dad.

> I have 4 Alexa 3 gen in all around my house and it's so useful btw I got them on Black Friday.

The Interaction concept is strongly (48%) connected to the Organisational Frontline concept. The comments revealed the user's experience of interacting with the organisational frontline.

> This would be a more natural interaction with your smart assistant than using wake words all the god damn time.

> I use both Google and Echo. I find Google much more conversational, as you mentioned.

> I do like the buttons on the do, making it handy many times to not use the waking word "Alexa".

4.3.2 Trust Theme

Trust is the second strongest theme in this research. The Trust concept is a compound of the words: trust, CIA, FBI, government, privacy, security, spying, safe, check, listening. These words were compounded based on the voice-based intelligent assistant's privacy risk and uncertainty problem from the concepts gained in the first analysis by Leximancer.

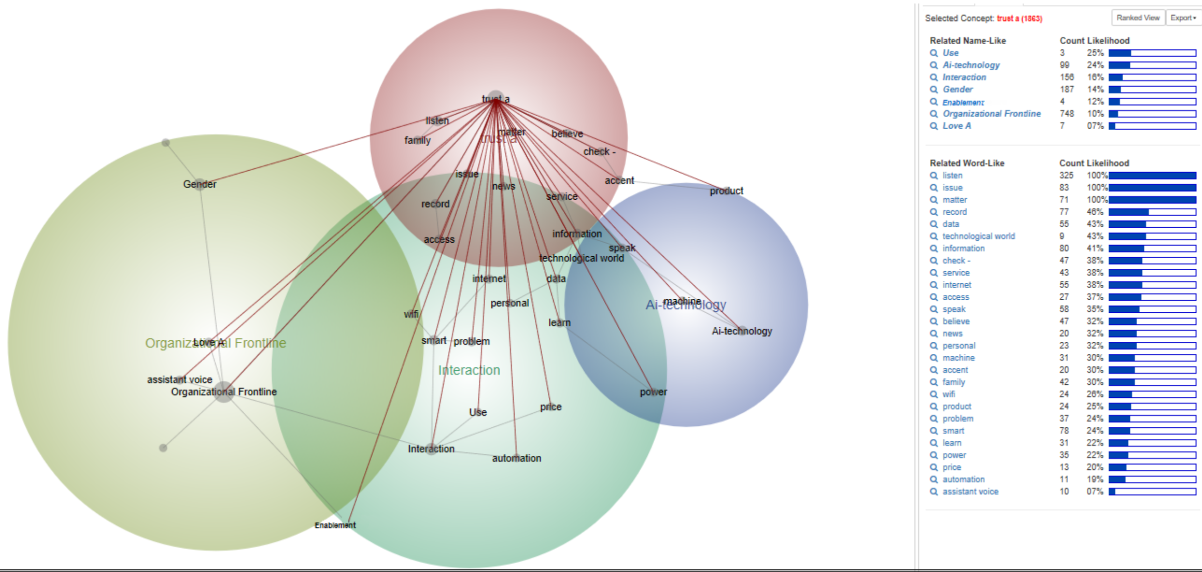

Figure 4-4: Trust Concept Map

Trust concept connections with other concepts reveal that there is a very strong relationship between the Trust and Listen (100%) concepts (see figure 4.4). It shows that the writer's biggest concern is about the intelligent assistants listening to their conversation. Referring to the comments illustrates this relationship in both positive and negative ways.

> For the most part, I have one question Alexa still needs to listen for keywords how can I trust it not to be recording before that we KNOW from the article you mentioned that you need physical access to make it into a bug but that was not what the article had to say alone it also mentioned that it still heard while in its standby phase it is unknown if that is transmitted at all.

> Really come one, with Alexa or any smart speaker even if they say it's not listening it is. always listening as a trigger word is needed as people need to say Alexa etc.

Also, a high co-occurrence of Trust and Issue (100%) demonstrates these two concepts come together all the time in the text. Issue refers to users' concerns about intelligent assistants because of contents of videos regarding privacy issues. As figure 4.1 shows the Issue concept is located at the overlap of the Trust and Interaction Themes that reflect how the user's perceived issues affect trust when interacting with the intelligent assistant.

> I'd rather use it and know all about the pros and cons. Folks who resist the tech for this issue (listening to user's conversations) should stay away from it, simple rule - don't use it, don't comment on it!

> I think they're both very good and I use both but I have one big issue with Google which is the speakers and music groups often keep disappearing which causes me a lot of frustration. This has been happening since November 2019 with poor excuses from Google and the issue still exists.

> It concerns me when people say "I have nothing to hide, so I am not worried". I am sure most of us have nothing to hide, the issue is really when someone has a small piece of information then misuses it or distorts it to their ends.

The third significant relationship is between the Trust and Matter concepts (100%). User's impress upon the importance of the related subjects to Trust and Matter concepts as demonstrated in the following comments:

> I have Google Nest Mini, and if I feel I need privacy I just pull the power-cord. Commonly if you are connected to the net and do stuff on the web, your privacy is always at risk no matter what service you use.

> No matter how much they say they can protect your data, you can't believe it. (I blew up my ESP32...)

Trust also strongly connected to the Record (45%) and Information (41%) concepts associated with the Interaction theme. Writers show different opinions about recording their conversations or abusing their information by intelligent assistants in their comments. Both concepts are related to privacy risk and uncertainty in interaction with the intelligent assistants that affect trust.

> If you have had enough of Google invading your privacy through Alexa or Amazon streaming etc, just throw the speaker out and scrub the software off your computer and I do mean uninstall and delete it not just unenroll or it will keep recording you. Also tell them in writing you NO LONGER CONSENT to their terms of service.

> Pretty sure the CIA is all about information over the internet so if it is connected to the internet it is connected to the CIA, same goes for your computer, cell phone and some newer model cars.

Moreover, the connections between the Trust and Record concept and the Trust and Information concept are that both concepts placed in the overlap of the Trust with Interaction theme, illustrating that privacy subjects (i.e., related to Record concept) and lack of information about AI technologies (i.e., related to Information concept) could trigger conspiracy theories which are likely to affect the willingness of people to interact with intelligent assistants.

> This is very interesting. But it is also very scary. Made me reflect on a few things I have been reading. I hope you don't mind me sharing it here and turning this into a discussion.
> 1. Further erosion of trust - Who is authentic? Who is recording our calls? Are every interactions of ours judged, coded, filed, filtered? By whom, to what effect?
> Google & others like it - 1, Humanity - 0
> 2. Google building its strategic moat - It feels like it wants to become the agent between every conceivable transaction, interaction for everyone in the world. The sum of these parts would be huge and possibly invisible to us. What happens with the data and the smarter algorithms? what use cases are there? should these things be even allowed with a view of possible vulnerabilities it can introduce for individuals, minorities etc.?
> Google-2, humanity - 0.
> 3. Trade-off - Pichai showed the use case of the query about business open time... For that information in exchange, he wants access to information about people's activities, preferences, behaviours. things that enrich the AI that could be put to purposes beyond our control.
> It is a mighty high price to pay for mild conveniences.
> Google - 3, Humanity - 0.
> 4. World's brightest brain power used to reduce relevance of humans - This is quite disconcerting. Apple, Google, Uber... the biggest companies in the world who require fewer and fewer people to earn more and more are doubling down on technologies that help reduce dependencies on humans. Stretch that logic and it seems as if the end game is Elysium/ colonial past - where there are a few essentials and many interchangeable/ replaceable.
> "The Dictator's handbook" has interesting things to say about such power dynamics.
> These technologies are geared towards creation of dictatorships.
> And if you look at what Marshall McLuhan says about technology and its impact on humans - he essentially says that technology defines us, not the other way round - it rings a certain level of inevitability to authoritarianism if we let these technologies flourish.
> Google and others like it - 4, humanity - 0.

The detail from the Trust concept demonstrates that there is a significant relationship between the Technological world concept (43%) associated with the AI-technology theme and Trust. Technological world is the compound of live or living and world (after the first run of the software, live and living were combined as living. In the next stage the researcher reran the software. The results showed high connectivity between living and world. The researcher returned to the comments in this stage to use them for managing data analysis. In most of comments writers pointed to ubiquity of technology in the world and because of that they compound as ‘technological world’). Writers believed that one of the prerequisites of living in today’s world is acceptance and trust in technology. The Technological world concept is located in the overlap of AI-technology and Interaction themes. It noted the presence of trust in interacting with AI- technologies. The same applies to the Learn and Power concepts.

> I honestly do not worry too much about it. I know we have to lose some privacy for convenience, but that is the world we now live in.

> You've lost your privacy COMPLETELY if you keep one of these turned on in your home. It is an "adaptive character-profiling computer algorithm" designed to learn " EVERYTHING ABOUT YOU ". Wake up people!

> Google is pushing these for free because they want to normalise the spying and mass data collection on Americans etc. I see the power play they are making and I would refrain from getting one.

One of the interesting points arising from this data are the writers' viewpoints about trusting in intelligent assistants in the role of the organisational frontline (Trust and Organisational Frontline relationship). One group of commenters believed that the producer companies design and produce intelligent assistants in a way that affects users (especially emotionally) to trust them. Plus, the producer is responsible for all of Trust’s subjects.

> As time goes by, I think we’ll see these devices take a greater role than they were initially marketed as and will become, like smartphones are today, a view into your private world (e.g. when video will be added). These devices are programmed to tell jokes and interact in human ways, and in doing so, they are programming us to trust them.

> But the less engaged we are, and the more passively we use them, the more they are being manipulated towards goals that are not in our best interests. These platforms undergo continuous changes and shifts that do not consult the user.

> Never trust an Alexa it can tell you what is programmed so it is not lying to you the programmer is lying to you. Why would you want anything like this in your house, have we become that lazy.

The next group of commenters were sure about the honesty of the intelligent assistants because of the reputation of the producer.

> Truth is security and privacy is essential and I can agree with you we all aught make it a priority but should it always be at Apple's and costs? I would that other companies follow suit, Apple or not, but I can understand why you're so advocating all things Apple but truth is we all can't and won't use everything Apple.

Another group of commenters were skeptical about trusting their intelligent assistants regarding the privacy subject and try to test it by asking the intelligent assistant directly. As intelligent assistants remain silent and do not answer the questions at all (lie or truth) users consider it a positive answer to not betray the user's privacy, the same as a similar condition in human-to-human interactions.

> When I said "Alexa, read me your terms of service," it turned off.
> Reply on comment:
>
> - I'm thinking it's because there's just too much text, but of course, that's not the real reason.
> - In my prediction and pronouncement, yes, the US government and Alexa, and all the Amazon voice command products are recording everybody's conversation here on the face of the Earth. If you don't want this happening to you at point blank range, I strongly advise everybody here on the face of the Earth not to buy these devices, they are one hit wonders. You can always tell what the answer is if you ask these devices these questions, and they either freeze up, or it shuts down on its own. Pretty obvious what the correct answer is, don't ya think? The correct answer is, "Yes, you are being recorded by Google, Amazon, Microsoft, Apple, the US Government, the CIA, and the CEO". Anyway, that's just me reading into these things especially what just happened when Alexa was acting toward you when you asked her those questions. There's a good chance that some of these computer technology companies who made these devices, and released them have some things to hide. Sorry for the long rant, just thought I'd tell you all here on the face of the Earth what the obvious answer was, yes, we are being watched, and recorded. Lesson learned, if you don't want to be secretly recorded with these devices, don't buy them.

> "Alexa, read me terms of service"
> My Alexa hears this from my phone, (Alexa is right next to my bed lol)
> Alexa: turns on, but then shuts off after question.
> My echo dot stopped when I asked for her terms of service.

> Alexa could be lying about telling the truth.
> Reply on comment:

- That's why it hedges by saying "I TRY to tell the truth." It's a fucking obvious spy app! People BUY Big Brother to spy on them? Read 1984 by George Orwell!

Alexa ignores the question are you recording this conversation
Me: I'll take that as a yes

Some commenters go even further and completely distrusted the intelligent assistant regarding the privacy issue irrespective of the answer.

> I doubt Alexa would ever say "Yes, I'm recording your conversation and sending it to the government." I also wonder...if she said "No, I'm not recording your conversation and sending it to the government", would you believe her, even though she was programmed to say that she always tries to tell the truth?

4.3.3 Interaction Themes

Interaction is the third important theme in current research. The Interaction concept is directly selected from primary Leximancer analysis. Interaction is one of the most substantial components of a human-to-machine relationship especially by humanising the machines. It also affects the human's experience of communicating with machines. According to the Interaction concept's connections map (Figure 4.5), there is a strong relationship between the Interaction and Use (100%) concept. It shows the effect of interaction on using intelligent assistants.

> This would be a more natural interaction with your smart assistant than using wake words all the god damn time.

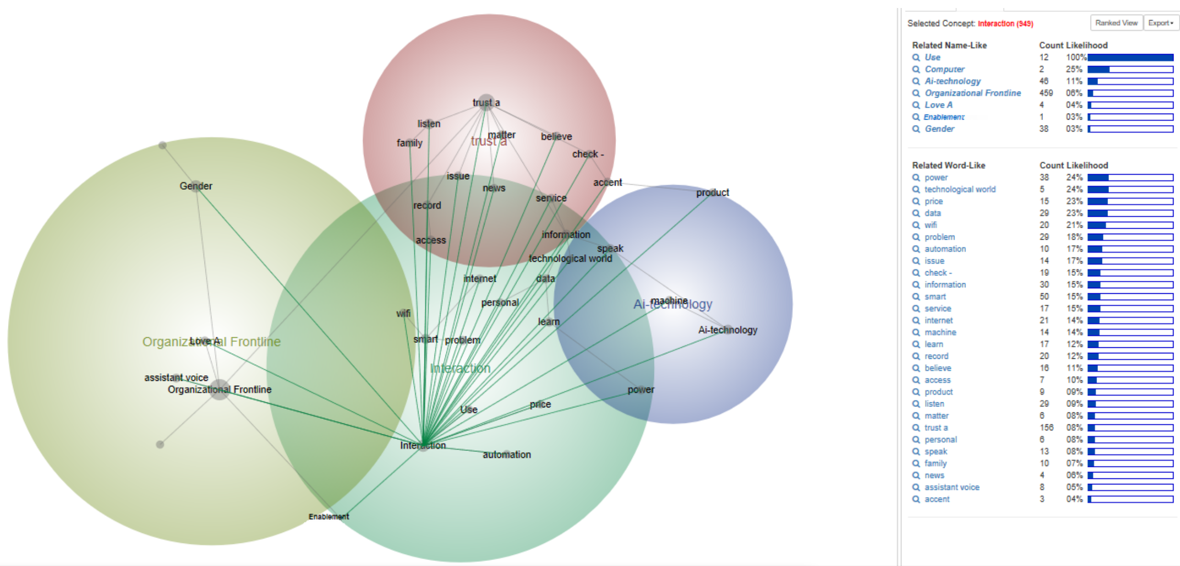

Figure 4-5 Interaction Concept's Map

The Interaction concept's connection map also shows a significant relationship between the Interaction and Power (24%) and Technological world (24%) concepts linked to the AI-technology theme. This demonstrates the effects of technology on interacting with the intelligent assistant, i.e. living in today's technological world increases interactions with machines, or technology can facilitate interaction or make it hard for some users.

> So Jonathan as for where I stand with the Google Assistance talking like a human I am of two opinions. First there are many disabled people in the world that for one reason or a other are unable to speak but can type, this technology can give them a voice to interact and that's great.

> I swear I treat her like a real person, even telling her "thank you" and she comes back with "you're welcome". I still want to be able to use the hands free calling, I live alone and it may be important that I'm able to reach out to someone if I need some assistance.

The relationship between the Interaction and Price concept noted that price acts as a motivation for people to engage with the intelligent assistant and interact with it.

4.3.4 AI-Technology Themes

AI-technology is the last important theme. Its connection map shows the relationships with a low significance, and that the most important ones are between the AI-technology concept and Learn (18%), Speak (17%), and Technological world (14%), which all are located in the shared zone of the Interaction and AI-technology themes (see figure 4.6).

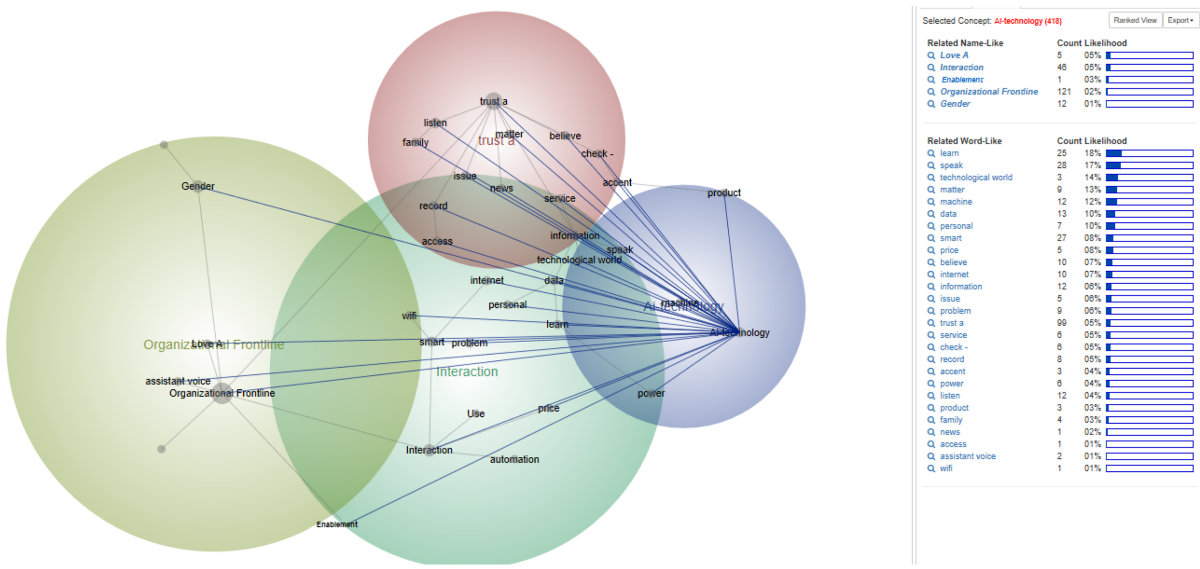

Figure 4-6: AI-Technology Concept Map

The relationship between AI-technology and Learn illustrates the learning aspect of the last generation of AI (intelligent assistants) and its effect on interacting with AI-technologies.

> I'm worry if I change to Alexa maybe she won't understand me because I'm not English native speaker. Do you think Google learns my language and Alexa doesn't?

> Also, it’s not beyond the realm of possibility to consider that these AI could learn how to read visual and auditory data on the frequencies ghosts reside on.

> There was no mention of the new Nest Minis on board AI chip. The nest mini can learn to do certain commands, like turn on/off lights without sending the request back to end servers (internet).

> It’s rather disconcerting to me to think that it’s possible that when we are not around our intelligent assistant s that these “ghosts” are able to talk to them. With ai being able to learn and store information to adjust their responses and perhaps their own thought processes that they could be getting filled with data from none sentient sources, data we have no knowledge of.

One of the superior features of voice-based intelligent assistants over other intelligent assistants is voice recognition and their ability to speak and communicate in a human-like way. Comments on videos show that the relationship between the Speak and AI-technology concept is not purely positive. The good experiences of interacting with voice-based intelligent assistants, which in turn create positive expectations, build a positive relationship between the AI-technology and Speak concepts. While the unfavourable experience of interacting with these intelligent assistants affects the relationship between the AI-technology and Speak concepts negatively.

> Tried to find a way to make use of this thing but I just can't. Speaking to a thing that can't even understand you well in any language and has limited functionality in my native language is taking more effort than just grabbing a remote or standing up and doing it myself.

> Imagine this technology in gaming, speak into your microphone to an npc and they understand what you say and respond correctly.

> I don't think people realize that sure, the AI might not get everything perfect, but if a business owner realizes they are speaking with an AI, they will just make sure to keep their questions short and sweet, so the AI can still book the reservation without any problems.

> Perhaps you (the tourist) can rent an AI assistant who acts as a translator, among other things; or you (the company) has one installed into your systems. Anyone who has worked at a hotel knows that booking reservations with people who don't speak English as a first language can be... frustrating.

Another issue that is mentioned by commenters is ethics in the relationship with businesses that use intelligent assistants, as these days machines become more human-like to a degree that it is hard to discern them from humans.

> That said, this is morally repugnant. We should, as customers, know when we are talking to a human or a machine.

Commenters want to be sure about interacting with a human or machine because of ambiguities about recording the conversations by intelligent assistants. Perceived risk and uncertainty resulting from AI-technologies affected trust, and as a result interacting with smart machines.

> It seems like this would break wire-tapping laws in states with two-party consent (such as CA). I'm assuming the human on the other end is being recorded, or at the very least their speech data is being fed back into the algorithm.

> Isn't it illegal to record a phone call in a dozen or so states without the consent of all parties? And in the rest one party to the conversation must consent. I assume this would fall under recording a conversation to make the tech work. What are the legal ramifications? Especially in states where all parties must consent? Even in the one-party consent states, who's consenting? The person who asked the assistant to make the call? Google? The AI itself? And maybe it would matter less if it was recorded just to complete the conversation and then deleted, but since when did Google ever delete anything?

Furthermore, commenters with previous similar experiences impacted on the perceived risk and uncertainty to trust in intelligent assistants and interact with them.

> And you're selling this info to 3rd party apps, #Google? That's what #Facebook did. Now we can be deep profiled down to our souls, and those who know (be they human or not) that profile know all the sweet spots: they can shape our thoughts. #Marketing is propaganda. Hell, it's #religion.

Also, commenters mentioned that AI-technologies have made machines more competent which leads to preferring them over humans to receive services. This pointed out the need for more investigation about human-to-machine relationships.

> AI is great, soon we will not be allowed to drive because we are not as safe or as good as self driving cars or work because we are not as efficient as AI and we will lose those functions because we do not use them on a regular basis. Hell, even making a phone appointment will be more efficient with AI so what exactly will be our purpose? Wall-E anyone?

4.4 Conclusion

Participants first engage with intelligent assistants due to WOM or enablement. After the first engagement, participants are gratified by the intelligent assistant's benefits (e.g., utilitarian, hedonic, and social benefits) which lead to starting the relationship and reengagement. Enabled anthropomorphic features by intuitive AI, on the one hand, increase intelligent assistant's benefits (ease of use, participant empowerment, information quality, etc.) which influence relational factors positively. On the other hand, anthropomorphic features (e.g., voice recognition) enhance privacy risk and uncertainty in the human-intelligent assistant relationship which affects relational factors negatively. However, research data shows that as there is not sufficient data and knowledge to assess risk, participants build and develop their relationships with intelligent assistants based on the gratifications they receive. Anthropomorphic features, by giving human characteristics to intelligent machines, facilitate the formation of emotional affinity by users and consequently build rapport simultaneous with trust that influences the human-intelligent assistant relationship. Moreover, acquired social and hedonic gratifications cause users to build affective commitment towards their intelligent assistants, which creates an emotional attachment to and involvement with a service provider.

Chapter 5 Discussion

5.1 Introduction

This chapter discusses the results of this research in the light of use and gratification theory, anthropomorphism theory, and social exchange theory. This chapter will explain the customer service experience of using intelligent assistants through the discussion of the effects of intuitive AI and its resultant anthropomorphic features. AI will be discussed in this chapter as a computational system that works based on algorithms and not as a general intelligence that was discussed by Turing (1950). Intuitive AI was selected based on the Huang and Rust (2018) classification of AI (see section 2.4) and is considered not equal with human intuitive intelligence. It will be argued that the customer service experience journey starts by engaging through either WOM or enablement. After first engagement, customers acquired gratification (e.g., mostly utilitarian and hedonic) and because of that then reengage with the intelligent assistant. Reengaging with the intelligent assistant affects AI functions (i.e., feeding algorithm to improve learning process) which results in building different gratifications for customers. Acquired gratifications by customers influence building and developing the human-intelligent assistant relationships. In turn, relational factors affect different dimensions of customer engagement. Besides, it will be described how anthropomorphic features impact the human-intelligent assistant relationship directly. Subsequently, mannerisms will be discussed to show how cognitive intelligence and AI's mannerisms build superior service experiences for customers when compared with human frontline employees. To conclude, a proposed model (figure 5.1) from the discussed results will be presented.

Note: This research findings show that apparently AI reaches to the artificial general intelligence. However, as it was mentioned before in Chapter 1, it is only users' perceptions of interacting with machines that display human characteristics (e.g., features, behaviour and trait) from a social science viewpoint.

5.2 Customer Service Experience

Intuitive AI and its resulting anthropomorphism have completely changed the perception of machines as they become more human-like (e.g., from intelligence, appearance, manners viewpoints). However, in some aspects (e.g., sharing common experiences or empathy), machines still exhibit machine features. Hence, machines cannot transfer a sense of interacting purely as humans, as they do not have empathy, or purely as machines, as they can learn like humans or demonstrate human mannerisms. Therefore, a customer's experience would be different in interacting with humans or nonintelligent machines. Results of this research show that perceived gratifications in the light of intuitive AI and anthropomorphism are the driver of human behaviour in human-intelligent machine interactions. Therefore, in the following sections, the effects of intuitive AI and anthropomorphism on customer service experience will be discussed further.

5.2.1 Intuitive AI, Anthropomorphic Features, and Gratification

Anthropomorphism's effects in the service domain have generally been investigated under consideration of two anthropomorphism and uncanny valley theories. However, the effect of anthropomorphic features on the customer service experience is still ambiguous. One stream (i.e., anthropomorphism theory) suggests that anthropomorphic features in service robots ease customer engagement (Blut et al., 2021; Epley et al., 2007). While another stream (i.e., uncanny valley theory) discusses mostly negative effects of anthropomorphic features on engagement and use of technology (Ho & MacDorman, 2010). Findings of this research support the positive effects of anthropomorphisms and illustrate that anthropomorphic features facilitate customer engagement and enhance the customer experience positively. However, the research data illustrated literature based on uncanny valley theory as well, since intelligent assistants that were studied in this research appear to be on the ascent and therefore positioned in the positive part of the uncanny valley diagram.

Users were gratified from communicating with intelligent assistants without considering they were machines. They experienced three kinds of gratification (i.e., social, hedonic, and utilitarian) that are established by the AI features of intelligent assistants. This research data illustrates that intuitive AI, due to giving anthropomorphic features (e.g., natural language processing (NLP), voice recognition, cognitive intelligence, etc.) to intelligent machines, creates the illusion for customers of interacting with a human that does not have some human defects (e.g., fatigue, being judgmental). This causes customers to experience gratifications in different ways compared with nonintelligent machines and humans. Customers were gratified through interacting with the intelligent assistant itself directly and not as a medium in human interactions.

Machine learning makes intelligent assistants intellectually more human-like (Wirtz et al., 2018). Intuitive AI provides learning power to intelligent assistants which causes them to be smart in a way similar to humans. In previous research humans perceived machines as intelligent because of the illusion of humanising the agent. In this research, it has been found that users anthropomorphised their intelligent assistants as 'humans' after perceiving they are intelligent. Users, for instance, consider their intelligent assistants as a human companion when they are playing intellectual games with them (e.g., Crazy Math or Jeopardy). In contrast, Huang and Rust (2018) discussed that anthropomorphised robots are perceived to be more intelligent by customers than non-anthropomorphic robots who are seen as merely machines. Also, Blut et al. (2021) suggested that users assign more human intelligence to anthropomorphised robots and they perceived them as more capable to deliver a service. This difference may be explained by the intuitive level of AI investigated in this research.

In the information and computer science field, Sung et al. (2007) studied the vacuum cleaner robot Roomba. They illustrated humans anthropomorphise and zoomorphise Roomba and treat it as a being (e.g., assistant, pet-like being, valuable family member) because of Roomba's independence to do cleaning tasks. Sung et al. (2007) explained that humans anthropomorphise and zoomorphise Roomba due to its competence in vacuuming and not machine learning. However, in this research the learning power of intelligent assistants in both cognitive and behavioural aspects affects participant's perception of intelligent assistants to anthropomorphise them as human, and to form an emotional affinity towards them. Moreover, Roomba is dedicated to one task (i.e., cleaning) with limited learning capacity, while this research investigated intelligent assistants that offer a variety of services with high learning ability.

Anthropomorphic features, especially cognitive intelligence (i.e., learning power), increase perceived utilitarian gratifications (i.e., cognitive and non-emotional outcomes of service). Intelligent assistants are the convenient way to receive a variety of services, from seeking information, to turning the lights on anytime anywhere. The cognitive intelligence of intelligent assistants enables them to perform efficiently and to facilitate conditions (e.g., learning to recognise different accents). This finding supports Zong et al. (2019) and Cheng and Jiang (2020b) who investigated seeking information (text, pictures, and videos) in social networking services and the effects of AI on building utilitarian gratifications through making the seeking of information convenient. However, in this research utilitarian gratifications were obtained mostly based on sending requests and receiving responses by voice. Besides, the findings of this research illustrate how a large part of hedonic value acquired by users is because of using

NLP and deep machine learning in intelligent assistants. Users acquired hedonic gratifications through interacting with intelligent assistants. Intelligent assistants can create enjoyment (i.e., construe hedonic gratification) in different ways for users due to being interactive systems. The voice recognition feature enables them to have reciprocal communicative interactions, such as telling a story or joke, and the cognitive intelligence feature enables them to play games with users the same as a human companion. These findings reflect Zong et al. (2019) who argued that social network services provide users with entertainment aspects, like social games and video sharing, and that by using them, users can gain hedonic gratification.

The importance of socialisation and entertainment in daily life highlighted the need for social platforms or interactive systems (Thackara, 2001). Brandtzaeg and Følstad (2017) suggested that in interactive and human-like systems needing entertainment and social relations are more significant. These findings identify the latent structures related to acquired social gratifications from media directly. This is inconsistent with current use and gratification literature, that explain acquired social gratifications were gained through communicating with other people by media (social interaction) or a sense of social presence (Brandtzaeg & Følstad, 2017; Cheng & Jiang, 2020a, 2020b; Dhir, Chen, & Nieminen, 2015). Users obtained social gratification from communicating with the media itself because AI makes intelligent assistants capable of having reciprocal communication with humans. Anthropomorphism resulted from intuitive AI building social interactions and social gratifications similar to human-human communications for users. Users even form an emotional affinity toward media and get emotionally involved. This may be a significant opportunity for businesses if they are able to get their customers emotionally engaged. To the best of my knowledge, there is no literature about evoking social gratification by machines as one of the parties in communication. Literature refers to social gratification as a subject that increases the interactions between users of media and other people (Jang & Liu, 2019; Vale & Fernandes, 2018). It also has been discussed that social media tools like social interactions and social presence could enhance social gratifications (Cheng & Jiang, 2020).

Findings from this study suggest that acquired social gratifications impact a user's engagement with intelligent assistants. Users are gratified by social interaction with intelligent assistants directly and not as a medium in human-human communications. People can have social interactions with intelligent assistants due to anthropomorphic features. Social interactions give users a sense of social presence that increases their engagement with intelligent assistants, especially lonely people. Users start to talk with intelligent assistants when they are alone and anthropomorphic features such as humanised voice give them a sense of social presence which results in more engagement. This research finding regarding the effects of social gratification on increasing user's engagement supports Jang and Liu (2019) study that social gratification affects intention to use for certain game player groups. In their research, game players obtained social gratification through social interaction with other human players by mobile augmented reality games. What makes this research different from previous literature regarding social gratification is the social interaction with intelligent assistants as one of the parties in interaction. In previous research, the technology was used for interpersonal communications and social networking (Chavez et al., 2020; Gan & Wang, 2015; Zong et al., 2019).

Intuitive AI and its resulted anthropomorphic features add social attractions (i.e., social or personal liking features), to intelligent assistants that make it more interesting for users to communicate with them. For instance, either a humanised voice or mannerism attracts users to communicate with intelligent assistants and consequently creates social gratification for users. Han and Yang (2018) illustrated that social attraction affects positively parasocial relationships and in turn continuance intention.

5.2.2 Intuitive AI, Anthropomorphic Features, and Engagement

Customers have different opinions regarding interacting with frontline employees in service encounters. Some people prefer not to have interaction with humans while others like to socially interact with frontline employees. Applying intelligent assistants could help businesses to empower their frontline employees to make the customer experience more pleasant and keep both groups of customers engaged. Intelligent assistants may transfer the sense of human-to-human interaction to customers who like to socially interact with frontline employees and others who prefer fewer human interactions, and build the best service experience for both. These results support Belanche et al. (2020) who propose the customer service experience of human or machine frontline depends on customer preferences of the level of social interaction with frontline employees. This also supports Lee and Cho (2020) research findings that suggest some people use smart speakers to 'escape from reality' hoping to get away from interpersonal relationships while maintaining social interactions. In this case, people substitute smart speakers for social interactions.

Different types of gratification are considered as motivations to use media (Brandtzaeg & Følstad, 2017). According to Brandtzaeg and Følstad (2017), most users apply chatbots because of the gratifications (utilitarian, hedonic, and social) they received when using them. They believed users applied chatbots for social and relational purposes and were perceived to be socialising with a human through texting (i.e., talking to someone via text or online chatting). The results of this research also shows that users apply intelligent assistants to socialise with and to avoid loneliness. AI makes it possible to have reciprocal conversations with intelligent assistants. Users place intelligent assistants in a human role (As they mentioned: *having another human voice at home*) and enjoyed talking with them.

Utilitarian motivations (affordable cost, functionality, information quality, quick access, and skill and knowledge) result in different gratifications. Most of these motivations lead to utilitarian gratification, but skills and knowledge, more than utilitarian gratifications, leads to social and hedonic gratifications. For example, smart intelligent assistants have many skills that facilitate life for users through voice-based interactions. Storytelling (e.g., bedtime stories for children) as one of their voice-based skills creates hedonic gratifications for users or gives users a sense of social presence and builds social gratification. This is in contrast to Lee and Cho (2020) who find that utilitarian motivations do not result in parasocial relationships, but are related to hedonic motives. However, this finding supports Mouakket (2019) study about motivational factors (e.g., perceived usefulness) effects on creating utilitarian gratification.

This research highlights the effects of gratifications on customer engagement. What differentiates this research's results from former studies is the application of intuitive AI and anthropomorphic features. AI makes technology more human-like and turns it from a medium of communication to one of the communication parties. Gratifications that users experience by using intelligent assistants to receive services causes them to prefer intelligent assistants to humans most of the time. Machine agents might be more impartial in problem-solving than human agents which leads to solving problems more effectively, thereby contributing to intense engagement (Cheng & Jiang, 2020b; Shyam Sundar & Kim, 2019).

This research illustrates how customers engage with intelligent assistants for different reasons (e.g., diverse motivations, social pressure, WOM, social presence, technological sophistication, etc.) and how they experience services differently.

5.2.1.1 Enablement

According to the use and gratification approach, different features of the media could satisfy a user’s different needs for gratification which leads to their use of media (Gan & Wang, 2015; Mouakket, 2019; Zong et al., 2019). This study proves that the first time most users engage with intelligent assistants is because of enablement (i.e., birthday gift, new year gift, or as an additional part of another shopping basket (e.g., people buy something else and receive intelligent assistant free or with discount)). After using it, and due to experiencing AI-resulted gratifications, users engage again with the intelligent assistant to address their needs. Predominantly utilitarian gratifications (e.g., convenience), followed by hedonic gratifications, tempt users to continue applying intelligent assistants. Hence users, often do not play an active role in making the decision to select their intelligent assistants based on their needs for the first time. This contradicts Katz, Blumler, and Gurevitc.M (1973) who assume users are not passive media consumers and that they play an active role in interpreting and integrating media in their life. Past literature emphasises that users are aware of their needs, and to address their special needs they select a media channel to gratify them (Abrantes et al., 2013), whereas this research's results illustrate other stimuli can affect media selection (e.g., receiving it as a gift) and decrease a user’s role in selecting media. Consequently, this research helps to develop use and gratification theory via investigating the machine's human-like aspects and its effects on the relationship between gratification and engagement.

5.2.1.2 Empowerment

Intelligent assistant’s anthropomorphic features empower users to be multi-tasking and independent which result in creating utilitarian and hedonic gratifications. Users can ask their intelligent assistant for a service they need while they are doing something else. For instance, users can ask for converting pounds to grams while they are cooking in the kitchen which results in experiencing utilitarian gratification. It also can build hedonic gratification for disabled users (e.g., blind people) due to providing satisfaction at being independent. This research follows Vale and Fernandes (2018) study who noted the interactive and collaborative nature of social media empowered Facebook users to develop their relationships as a fan with their favourite sports team. They suggest that empowerment affects a user’s social interactions (e.g., fan-to-fan or fan-to-sports team) which could result in social and hedonic gratifications. This finding also reflects Martindale and McKinney (2019) who argued that for women, empowerment resulting from the ability to sew leads to utilitarian and powerful social gratifications. Empowerment gives women confidence in appearance and skill, etc.

5.2.1.3 Ease of Use

Anthropomorphic features of intelligent assistants make using them easy which results in utilitarian and hedonic gratifications. In face-to-face service encounters, human frontline employees prepare the service for customers, while in remote service encounters customers need to have enough technological knowledge to apply the service themselves. However, anthropomorphic features close the gap between human-to-machine interactions to human-to-human interactions and increase ease of use of intelligent assistants especially for old and disabled people. People are able to receive services from intelligent assistants easier than other technologies which create utilitarian and hedonic gratifications for them. This is consistent with Ramirez-Correa et al. (2019), who found the hedonic information system's ease of use contributes to the utilitarian value through affecting perceived usefulness, and additionally perceived enjoyment contributes to hedonic value. The easier a technology is to use the more it is perceived to be useful (Cho & Sagynov, 2015).

Blut et al. (2021) presented a meta-analysis of physical robots, chatbots, and other AI and noted that ease of use has not been investigated sufficiently in robot studies. They propose that the positive effect of anthropomorphism on ease of use is expected as interacting with human-like robots makes interactions more natural and raises the perceived ease of use. Findings from this research shows that anthropomorphic features, specifically voice activation, increase ease of use as users can simply talk with the intelligent assistant rather than texting. A high level of perceived ease of use creates utilitarian gratification for all users although for old and disabled people it also establishes hedonic gratification through giving them the joy of being independent to do their work.

5.2.1.4 Word of Mouth

Environmental factors (e.g., store atmosphere) in service encounters affect perceptions of service outcomes. Positive effects of environmental factors bring about a higher utilitarian and hedonic service value assessment (Babin et al., 2005). In this research, most participants, after talking about their intelligent assistants with other people (i.e., WOM), have shown them their intelligent assistant's functionality (i.e., an environmental factor) which leads to building utilitarian and hedonic gratifications and in turn engagement. While previous research considered WOM as post-consumption outcomes that resulted from customer satisfaction or a positive experience (Babin et al., 2005; Chavez et al., 2020; Paul, Kang, & Haile, 2020). In this research it works also as pre-consumption stimuli. For instance, when users talk about the hedonic value of their assistant with their friends and ask their intelligent assistant to tell a joke or sing the happy birthday song for them, second-parties will experience hedonic gratification which could result in buying and using intelligent assistants.

Obtained gratifications persuade users to suggest intelligent assistants to other people or buy them as a gift (social pressure) to give them joy. It demonstrates how a positively experienced gratification by a customer will lead to sharing their experience via WOM. Research results especially demonstrated acquired hedonic gratifications significantly affect reuse intention and WOM. Users gratified by hedonic benefits, like telling jokes or asking silly questions to test intelligent assistant's cognitive intelligence (i.e., resulted from anthropomorphic features), or those who enjoyed the convenient and utilitarian benefits of intelligent assistants suggest using them to other people. This result supports Babin et al. (2005) study about face-to-face WOM. They believed customers illustrate service experience outcomes in terms of utilitarian and hedonic customer service values which results in post-consumption outcomes like satisfaction and customer WOM. This research finding also supports the findings of Paul et al. (2020), Pang (2021), and Chavez et al. (2020) regarding online WOM that find hedonic value and gratifications positively impact eWOM in virtual communications. They focused on the emotional value effects on increasing technological service use. In all of these studies, people received emotional value and hedonic gratifications through using technology but as a medium between them and other people. However, intelligent assistants, gratifications are obtained from technology directly due to its anthropomorphic features. These results also support Lee and Cho (2020) findings that hedonic gratifications (obtained from machines) affect the intention to use machines.

Giving or receiving a recommendations to/from others about an intelligent assistant, and being exposed to their functionality simultaneously, and positively affects experiencing gratification. When people recognise the benefits of the intelligent assistants (i.e. utilitarian and hedonic value) for the first time they are gratified by their function which leads to customer acquisition. Therefore, it is appropriate to suggest that WOM affects gratification and intention to use through the mediating role of gratifications.

5.2.1.5 Reuse Intention

Resulted gratifications of fulfilling needs form a user’s perception motivates them to engage with the technologies (Ji & Fu, 2013). As mentioned before in this research, the first time participants engaged with intelligent assistants is through either WOM or enablement (see sections 5.2.2.1 and 5.2.2.4). Then, their positive experience of the engagement with the intelligent assistant due to the obtained gratifications increases reuse intention to engage again with the intelligent assistant. Intention refers to a person's subjective probability to perform a behaviour (Cheng & Jiang, 2020b), while engagement is the act of being involved with something. Users gained utilitarian gratifications by using intelligent assistants mostly because of having quick access to service, information quality, intelligent assistant’s functionality, and their skill and knowledge which enhance the user’s intention to reuse intelligent assistants. Anthropomorphic features make it convenient to get access to services (e.g., speaking instead of texting, having 24/7 access, etc.) and obtaining utilitarian gratification which results in increasing the intention to reuse intelligent assistants to receive services. Findings identify utilitarian gratifications have a positive effect on reuse intention, and gratifications which are obtained from the intelligent assistant’s technological superiorities increase a user’s engagement with intelligent assistants. This follows Zong et al. (2019) findings regarding social media that create utilitarian gratification for users by allowing access to and exchanging information conveniently. They mention that when a user’s needs are satisfied through the social network service, they are more willing to reuse them.

A positive sensorial experience raises the intention to reuse intelligent assistants. Sensorial experiences increase expectations compared with similar alternatives that engender greater customer engagement (Lashkova, Anton, & Camarero, 2020). Altschwager, Conduit, Bouzdine-Chameeva, and Goodman (2017) illustrated that there is a significant relationship between sensorial experience and customer engagement. This research concurs with this finding and identifies that a reason behind that is anthropomorphic features. Intelligent assistants interact and communicate in a human-like way due to anthropomorphic features, which lead to a more pleasurable and convenient experience for the user and results in further intention to reuse and engagement.

5.2.1.6 Social Presence

Anthropomorphic features in intelligent assistants enhance the sense of social presence for users as they consider their intelligent assistants another person in their home who they can interact with. These characteristics (i.e., NLP, voice recognition, humanised voice, cognitive intelligence, etc.) could satisfy social and hedonic needs which are significant especially for those who need interaction and joy (e.g., lonely people). This result supports Kim et al. (2013) and Blut et al. (2021) findings that anthropomorphism arouses a sense of social presence and leads to improving social interaction. Kim et al. (2013) argued the effect of social presence in human-to-robot interactions on enjoyment and trust. They suggested gratification may result from higher social needs that could be fulfilled due to interacting with the robot. However, this research proposes that social presence is evoked by anthropomorphic features which shape social and hedonic gratifications for users through the feeling of having the company of another social entity during their interaction with the intelligent assistant.

Cheng and Jiang (2020b) and Xu et al. (2012) illustrated that social presence is a significant type of social gratification. It could facilitate interactions within social circles and social networks by giving a psychological sense of connecting with other humans. This research's results show users acquired social gratification from social presence and social interactions with intelligent assistants. AI and anthropomorphic features increase social presence for intelligent assistants, and in turn, give them a sense of communicating with another human and build social gratification. The research results also propose that mannerisms and the way that intelligent assistants behave, bring social gratification to users.

Moreover, a sense of social presence affects perceived gratifications especially hedonic gratifications. A sense of social presence due to anthropomorphic features gives users the illusion of interacting with another human and builds social gratification for them, especially for lonely people. In addition, a sense of social presence in playing with intelligent assistants or interacting with them provides a sense of playing or talking with a human friend which enhances hedonic and social gratification, or users enjoy listening to a woman's voice in their home. In this research social presence is considered one of the antecedents of engagement that affect perceived gratifications. This is different from Cheng and Jiang (2020b) and Xu et al. (2012) research that concluded that social presence was an important social gratification and that it affects reuse intention.

5.2.2 Mannerism

Humans construct and mold intelligent machine's behaviours through training the AI systems by active human input and passive human behaviour monitoring. A machine's mechanism to generate behaviour relates to both the algorithm and its environment (Rahwan et al., 2019). An intelligent assistant's behaviour (e.g., mannerism) is shaped and developed according to both a predefined algorithm (e.g., becoming silent when someone asks prohibited questions like sexual questions or how to commit suicide) and environment (e.g., each users' behaviour or manner). Created mannerisms due to intuitive AI can affect a user's experience and engagement depends on their behaviour positively or negatively.

Mannerism has been considered in three aspects by users. First, it is much easier to ask a machine to do simple and redundant tasks that will be annoying for humans. Second, users can ask any kind of questions without being worried that they will be judged, humiliated, or have the question disclosed to others. In other words, people can talk to intelligent assistants more freely than to a person. Third, intelligent assistants, owing to AI, are polite and behave based on the planned moral norms which cause people to accept and trust them better.

Intuitive AI and anthropomorphic features allow intelligent assistants to behave more human-like, while excluding unpleasant human behavioural characteristics. Brandtzaeg and Følstad (2017) mentioned that in their research only one participant preferred to talk to a chatbot about serious issues rather than a human because it is easier. While in this research intelligent assistants are preferred over humans and are considered more reliable and safer than humans in communication since they are nonjudgmental; they do not get angry at you, or they do not disclose your information, etc. These ethical features build a perception of moral competence for users and shape trust based on mannerism. This result supports Malle et al. (2019) who noted robots can avoid moral criticism in human-robot communication by remaining inaudible and having a calm and nonjudgmental tone which increases moral competence. They investigated robot behaviour and key aspects of robot ethics. However, this research studies the human behaviour and experience of interaction with intelligent assistants that present limited ethical characteristics.

Mannerism, as an anthropomorphic feature, influences relational dimensions also through verbal acknowledgment. The way that intelligent assistants interact with humans can build rapport and trust. This finding supports Wirtz et al. (2018) who believed robot design (i.e., gestures and verbal acknowledgment) can foster building rapport. Mannerisms causes users to perceive intelligent assistants as moral and ethical, and as a result, they believe intelligent assistants as they believe humans. It enhances building rapport (e.g., speaking with an intelligent assistant as a friend or saying thank you to an intelligent assistant) which supports Blut et al. (2021) who argued that due to anthropomorphism, people perceived robots as more sociable and life-like which increased the feeling of social connectedness. Building rapport simplifies the formation of emotional attachment by making it easier, more enjoyable, and meaningful. In an AI context, Qiu et al. (2020) argued that in less mature relationships, building rapport could help to form trust and enhance customer service experiences. This research agrees with that and highlights that building rapport establishes a positive psychological environment which leads to forming trust.

This research shows the perception of moral competence due to programmed mannerisms in intelligent assistants, but in reality there is not enough evidence in the data collect for this research to show all of the dimensions of moral competence. In this research moral norms, moral vocabulary, and moral judgment are recognised, however, these three dimensions give users the perception of moral competence which causes trust to form. Computational learning algorithms help smart machines to learn and develop human norms that lead to enhancing perceived moral competence and building trust. Learning algorithms also make intelligent assistants able to learn everyone's behaviour and mirror it back to that person. In addition, intuitive AI causes intelligent assistants to recognise uncommon questions (i.e., based on predefined norms and moral vocabulary) and stay silent which increases perceived moral competence. This finding supports Malle et al. (2019) who believed new learning algorithms will be needed to make robots able to learn human norms and the required language for moral discourse.

Moreover, perceived mannerisms affect social gratification as a participant mentioned: "*he is getting much more respect than he deserves in communicating with the intelligent assistant*." Mannerisms cause machines to become similar to humans from behavioural aspects and users could benefit from more human-like social and relational communications. It also amplifies the sense of a social presence from intelligent assistants and makes them more human-like which in turn leads to better social interactions and gratifications. Participant 7 explained how his intelligent assistant learns from their family manners and responds back in a similar manner to the individual which creates a high level of social presence:

> The constant battle between my wife and I is that it uses her manner. She jokes that google home likes me better and does not like her because it always says like if I for example want to run a timer I'll say please set a timer and it'll say here you go it is a timer for 20 minutes or something like that where if she just says set a timer, it sets the timer and doesn't say anything back to her. Yes, she thinks in the favour that I have a girlfriend or something (P7).

Araujo (2018) confirmed that anthropomorphic design cues enhance social presence for conversational agents by triggering a user's perception of anthropomorphism. He discussed how applying intelligent frames, like interaction style (dialogue) and messaging interface, affect the perception of social presence. This research suggests that intuitive AI adds mannerism to anthropomorphic features of intelligent assistants. Mannerism influences social presence by making machines able to behave like humans in a voice-based context. Users like the way that intelligent assistants behave like them or can learn and repeat back their good manners to them. For instance, being polite makes intelligent assistants more like humans and causes users to enjoy having social interactions with them. In turn, having social interactions with a human-like entity builds an emotional connection and affects the relationship positively. This is in contrast to Cheng and Jiang (2020a) who found that participants preferred communicating with a human rather than a chatbot.

During the literature review, any literature that investigated mannerisms in intelligent machines or its effects on the user's behaviour was not identified. Awad et al. (2018) studied moral machines in the computer science context to measure a user's moral preferences in designing machines, and Malle et al. (2019) investigated identifying demands for human norms (e.g., format of norms and their learning algorithms) in artificial agents. In this research, mannerism is investigated as a new effective anthropomorphic feature of human behaviour that intuitive AI adds to smart machines.

5.3 Customer Service Experience and Customer Engagement

The pleasant sensorial experience of interacting with intelligent assistants resulting from anthropomorphic features encourages users to engage with the intelligent assistants. Customers experience different forms of gratifications through applying intelligent assistants to receive services. This research proposes that experienced gratifications (utilitarian, hedonic, and social) positively affect the engagement and reuse intention of intelligent assistants. On the one hand, the findings challenge Cheng and Jiang (2020b) who showed hedonic and social gratifications did not have a significant effect on continued use. They proposed that AI could bring varieties of gratifications, information needs and entertainment for users, while AI can also bring privacy risk about misusing a user's personal information. According to their data, increasing privacy risk and uncertainty caused users not to continue to use chatbot services. Whereas this research's findings show AI brings privacy risk and uncertainty regarding listening to a user's conversations which makes users cautious, but simultaneously AI, by adding anthropomorphic features, affects trust and increases intention to reuse intelligent assistants. Anthropomorphic features create benefits and gratifications for users that cause them to accept the privacy risks and a willingness to continue to use intelligent assistants. As participant 9 mentioned *"I do not care someone spying on me, as technology brings me more fun"* whereby fun in this research is construed as the hedonic gratification. On the other hand, this supports Mouakket (2019) and Xu et al. (2012) research's findings that showed obtained utilitarian and social gratifications increase intention to use. This research findings support previous studies about mechanical and analytical AI-based service encounters and challenge intuitive AI-based service encounter studies. This study proposes that anthropomorphic features of intelligent assistants significantly affect the user's perceived gratifications and experience of them.

5.3.1 Privacy Risk and Uncertainty and Trust

Privacy risk and uncertainty is present in human-human or human-machine relationships associated with the disclosure of personal data. In an intelligent assistant-to-customer interaction, intuitive AI creates privacy risk and uncertainty regarding the pooling and storing of a user's data to feed AI algorithms. But due to a lack of AI knowledge and ambiguous privacy policies, users cannot have any idea regarding the true safety of their data.

In human-to-human interactions trust acts as a mitigator of risk and uncertainty in the relationship (Guinot et al., 2014; Tsai & Hung, 2019), and in the absence of trust (e.g., in first interaction) contract or social norms could act in the role of trust to minimise risk (Arrighetti, Bachmann, & Deakin, 1997).

In human-nonintelligent machine interactions customers trust in the human operator, service provider (brand) or technology. Customers trust in non-intelligent machines because of their competence to prepare information. Another explanation is that customers trust in the machine due to the human operator that handles the machine (Lee & See, 2004). A company's reputation or the presence of a third-party seal also cause customers to trust in nonintelligent machines. Nonetheless, Kim, Ferrin, and Rao (2008) argue that when there is a perceived privacy risk and uncertainty, for example a transaction risk during online shopping, the presence of a third-party (i.e., service provider) did not affect the customer's trust in the vendor to exchange the product if needed.

However, when machines become human-like there is a need to explore how social behaviour and responses from human-to-human interactions translate to human-to-intelligent machine interactions. More than having physical human-like features, intelligent assistants show human internal aspects (e.g., honesty and mannerisms) in the light of intuitive AI, which can affect customer perceptions of intelligent assistants' future behaviour and judge the risk versus benefit of exchange. Atkinson and Clark (2013) also suggest a need to understand how humans find important internal states (e.g., credible signals) of autonomous agents for judging trustworthiness.

This research asserts that anthropomorphism is a key element of human-intelligent machine relationships and evokes different forms of trust to be formed. Anthropomorphic features enhance competence, reliability, credibility, and benevolence in intelligent assistant-human relationships, which can affect the perceived privacy risk and uncertainty and whether to apply intelligent assistants or not. What makes this research different from previous research is: anthropomorphism effects on relational factors through building gratification (e.g., anthropomorphic features by creating utilitarian gratification enhance competence and credibility and through building social gratification boosts benevolence). These gratifications are mostly gained from human-machine communications or sometimes through brands.

Anthropomorphic features increase the competence of intelligent assistants (e.g., by giving cognitive intelligence to machines that can remove human errors due to stress or fatigue) and make their service experience acceptable to the extent that users prefer intelligent assistants over humans. It also causes intelligent assistants to work more precisely, based on algorithms and programs, which gives a sense of credibility and competence to users and increases trust. This result supports Kim et al. (2013), who illustrated in the human-robot relationship context humans felt greater trust towards a robot if they perceived greater human-likeness, intelligence, and social presence in robots than humans. It also supports Chérif and Lemoine (2019) who mentioned voice-based human-to-machine interactions boosted perceived credibility and competence. Intelligent assistants also are perceived as credible due to the brand of service provider (e.g., users consider Siri credible as it is an Apple product). Users trust technology as they consider the brand credible based on its reputation. This finding reflects Lassoued and Hobbs (2015) study that brands, by showing they have the ability and willingness to deliver what they promised, create brand credibility which results in brand trust. They also argued that the firm's previous activities or a customer's experience of the brand affects brand reputation, which affects brand trust and in turn brand loyalty.

Intuitive AI gives the opportunity to intelligent assistants to imbue the highest level of human-likeness and social presence to users. Anthropomorphic features resulting from intuitive AI increase the human-likeness of sensible intelligent assistants which result in enhancing reliability and benevolence. Intuitive AI and its anthropomorphic features raise reliability because of increasing a machine's abilities and transferring the sense of interacting with a human (e.g., mannerism), and enhancing benevolence by building emotional affinity for users. previous research investigated various dimensions of trust in human-machine relationships except for benevolence (Chérif & Lemoine, 2019; Kim et al., 2013; Madsen & Gregor, 2000; van Pinxteren et al., 2019). This research's finding shows benevolence in the human-machine relationship. This layer of trust comes up in the human-machine relationship because of anthropomorphism and attributing brand benevolence to intelligent assistants.

Anthropomorphic features trigger emotional affinity which leads to a sense of benevolence towards humans. Moreover, when customers perceived high responsibility (e.g., social) by a brand, they considered it benevolent. This research endorses Lassoued and Hobbs (2015) findings. They discussed how perceived brand benevolence affects brand trust and brand loyalty which leads customers to buy and consume a service or product from that brand. This research suggests that brands can deliver their brand credibility and benevolence in the offered products or services through building gratification for customers. However, in the human-human relationship a credible brand can be fostered by good employee communication and their ability to fulfil brand promises (Anees-ur-Rehman, Wong, Sultan, & Merrilees, 2018; Karanges, Johnston, Lings, & Beatson, 2018), whereas reviewed literature doesn't show any effect of brand credibility on employee credibility (i.e., frontline employees would not be considered credible due to working for a special brand). Consequently, anthropomorphic features affect forming different trust dimensions based on the acquired gratifications, which influence a customer’s judgment of privacy risk and uncertainty.

For tech-savvy users, the privacy risk and uncertainty associated with the intelligent assistant is a technology feature accepted in exchange to receive gratifications that form a type of trust as if it were blanket trust. However Blois (2003) argued that seldom can we apply blanket trust towards another party as trust is a multidimensional construct, and one party would trust completely in one dimension while distrusting in another dimension. This research supports this dimension as calculus-based trust and the results show that as users acquired gratifications they perceived there to be no risks and build a type of trust that provides with them the impression of blanket trust. Experienced gratifications and different dimensions of trust would affect each other reciprocally (e.g., competence can result in utilitarian and hedonic gratifications and experienced gratifications can enhance perceived competence).

Another group of users accept the risks of having no control over their privacy in the relationship with their intelligent assistants to obtain gratifications. They accept the privacy risks in the hope of fulfilling their expectations. This research shows that users rely on blind trust to develop their relationships because of receiving utilitarian and hedonic gratifications that result from the competence of intelligent assistants. Perceived competence gives confidence to users to build trust and to use intelligent assistants. Confidence, blind trust, or hope are a passive form of expectation that demonstrate a high degree of trust. This result supports Harwood and Garry (2017) who argued trust would be an indicator of confidence when the service system is technically complicated and there is not enough knowledge and understanding about the service system. This research suggests that intuitive AI enhances intelligent assistants' competence, which leads to being perceived more confidently and as low risk with a high propensity to trust.

At the other end of the trust spectrum users also could form distrust, because of the probability, that the AI assistant is listening and reduce their interactions from none to limiting usage when their perceived costs of privacy risk and uncertainty surpass the benefits. This finding supports Liu et al. (2017) who argued how in online service encounters, distrust enhances a customer's negative emotions and fear towards a service provider, which decreases their intention to transact as they wish to protect themselves from future risks.

Chan and Yao (2018) argued that in the presence of distrust, social attachments (i.e., our friends and our friend's friends) create assurances to drive exchange in human-human relationships. This research also supports their findings in human-machine relationships. It shows distrustful users who build social attachments with their intelligent assistants, due to anthropomorphic features, continued their exchange with the intelligent assistant. However, they limit their interactions with the intelligent assistant but do not terminate their interactions.

> Well, it's funny because I'm kind of like justifying Siri like it is my friend […].So I'm not saying that Siri, is a person, or is a spy listening but it means that she is listening and she's gathering information. […] So for me, I have limited my interactions with Siri a lot. So for instance, when I know that Siri is around I am a bit more cautious about what to say (P1).

But distrustful users who do not feel a social attachment with the intelligent assistant prefer to end the relationship. They would rather substitute something else for their intelligent assistants to receive gratifications.

> It really didn't seem to do anything that I just wouldn't have access to with the computer […]. But I also started getting uncomfortable at the idea of having something that's listening to me all the time in the living room […] So I ended up stopping using it (P21).

However in reality, there are not any differences between personal computers and an intelligent assistants functions (i.e., working based on the algorithm). The only thing that makes them different is anthropomorphism. Due to anthropomorphic features users consider the intelligent assistant as a person who listens to them while Google and other companies can collect everyone's data on personal computers too. People feel discomfort as they feel the presence of another person in their life.

The main logic behind calculative trust is a rational assessment of rewards and punishments (Poppo et al., 2016). Users are aware of intelligent assistants' privacy risks and uncertainty, but due to perceiving greater benefits (i.e., gratifications) they could build calculative trust to continue their relationships with intelligent assistants. Intuitive AI and its resulting anthropomorphic features increase the rewards for users by building gratifications to the extent that sometimes users forget about privacy risks. In that case calculative trust would move to blind trust.

Previous research explained how calculative trust is based on expectations of the future economic value of transactions, and it is rational decision-making based on uncertain conditions (Poppo et al., 2016; Reich-Graefe, 2014; Susarla et al., 2020; Williamson, 1993). However, this research shows that users form calculative trust not only based on economic value but also based on their expectations to receive hedonic and social gratifications, which are mostly of emotional value, not economic.

This research suggests that when customers do not have enough information to make a rational decision based on assessing their privacy risks, they decide based on perceived gratifications. Customers trade their privacy for gratification. This supports Reich-Graefe (2014) who argued that calculative trust, under the condition of bounded rational decision-making, is adopted as the best choice to proceed based on incomplete information. Consequently, evolving human-intelligent machine interactions are the result of the effects of trust, anthropomorphism and gratification on each other.

5.4 Relational Factors

5.4.1 Rapport and Emotional Affinity

Anthropomorphic features of intelligent assistants evoke positive emotional feelings in users which positively affect relational factors and their intention to reuse. Some users find they have an emotional affinity towards their intelligent assistants and they build rapport. Anthropomorphic features make intelligent assistants able to gratify users (e.g., singing a song (i.e., hedonic and social) for them or talking with them (i.e., social)) which may lead to building emotional feelings and rapport. This supports Qiu et al. (2020) research finding that illustrates how rapport can form in the human-robot relationship but is different from the human-human relationship. However this research's result challenges their result by showing anthropomorphic features cause users to form rapport similar to human-human relationships (e.g., interacting them as a friend).

In addition, building emotional feelings and rapport simplify and strengthen human-machine relationships that result in a better service experience. Previous studies discuss this as relational mediator dimensions (i.e., positive affect and rapport) in the anthropomorphism and service experience relationship (Blut et al., 2021; Bolton et al., 2018; Qiu et al., 2020; Van Doorn et al., 2017; Wirtz et al., 2018). They explained positive affect as positive feelings and emotions, which can elicit enjoyment, pleasure, and warmth, and considered rapport as a personal connection and an enjoyable interaction between customer and robot. This research supports their findings regarding the positive effects of anthropomorphism on relational factors. However, it illustrates that anthropomorphic features affect relational factors and in turn the customer service experiences through perceived gratifications. Anthropomorphic features build emotional affinity between users and intelligent assistants (e.g., as mentioned by participant 11: "*The way that it talks to you. So often you'll ask Alexa, what's the time or Alexa, what's the weather and it'll say have a great morning or have a great night or enjoy the sunshine today and those things are nice"* and participant 24: "*We find ourselves saying thank you or apologising if we didn't get it done right. She became like a presence in our kitchen"*) that lead to building hedonic and social gratifications. The resulting hedonic and social gratifications from anthropomorphic features lead to intensifying relational factors (e.g., rapport, trust, commitment).

5.4.2 Trust

An intelligent assistant's voice and the way they talk affect the human-machine relationship. Humanised voices of intelligent assistants influence trust perception. A humanised voice affects users emotionally (e.g., giving gender to intelligent assistants based on having a male or female voice and calling them beautiful lady, etc.) and gives them the feeling of interacting with a human which increases trust towards a machine. This research supports Chérif and Lemoine (2019) who argued how the effects of a synthetic voice compared with text significantly enhances the feeling of trust in human-to-robot interactions. Also Araujo (2018) who noted that applying human cues could affect relationships building by enhancing emotional connections. He believed the assistant's name and even the language style can be manipulated to change user perception. This research's findings support the effect of language style as participants mentioned that they love their intelligent assistants and want to start or end their day with their intelligent assistant's good morning or good night conversation. But this research also shows that the effect of using humanlike names are not significant as users have similar feelings and behaviours about Google Assistant (with a machinelike name) compared with Alexa (with a humanlike name). The reason behind this might be that other anthropomorphic feature (e.g., voice) are strong enough to give social presence to intelligent assistants and that compensates for a lack of having a human-like name to simulate a machine as a human. Companies give the opportunity to the users to change the voice (e.g., male or female voice, celebrity's voice) which causes them to form an affinity towards the intelligent assistants, while due to branding they do not let customers change the intelligent assistant's name.

5.4.3 Commitment

Anthropomorphism affects a customer's cognitive and emotional perception of their relationship with a machine. It introduces a commitment construct in human-machine relationships that are close to human-human relationships through giving human characteristics (e.g., learning power, mannerisms, etc.) to machines.

In human-human service encounters customers become committed to service providers due to the utilitarian, hedonic and social benefits or rewards they receive (Kim & Kim, 2020). However, in human-nonintelligent machine relationships, customers are committed to the service provider only due to receiving utilitarian and hedonic service outcomes (Bilgihan & Bujisic, 2015; Rajaobelina, Brun, Tep, & Arcand, 2018). Previous research argued that in human-nonintelligent machines there is no significant relationship between social value and commitment (Bilgihan & Bujisic, 2015; Pura & van Riel, 2005; Rajaobelina et al., 2018). Nonetheless, this research argues that in human-intelligent machine relationships, anthropomorphic features empowered intelligent assistants to behave like a human. Human-like features resulting from intuitive AI create utilitarian, hedonic, and social gratifications for users, which influence calculative and affective commitment in an intelligent assistant. The research findings show that perceived social gratifications affect affective commitment in human-intelligent assistant relationships. This finding contradicts Poushneh and Vasquez-Parraga (2019) who argued there is no relationship between perceived social value and affective commitment regarding smart products (e.g., smart phones). This is different from this research finding, as, in this research, social gratifications are the result of human-intelligent assistant interactions, and intelligent assistants are one of the interaction parties while Poushneh and Vasquez-Parraga (2019) investigated smart devices as a medium that facilitate human-to-human social interactions.

Customers become committed to technology (i.e., intelligent assistants) calculatedly and affectively rather than to the service provider, due to the illusion of interacting with a human. They also apply all human-human relationship rules to their relations. Customers build emotional attachments with a technology that leads to more engagement. As a result, it leads to a deeper relationship between the organisation and its customers indirectly, because AI-based frontline employees are not independent and will not leave the organisation and take customers with them. Moreover, since anthropomorphic features give the most respectable human characteristics to the intelligent assistants while eliminating human defects, users prefer to interact with intelligent assistants instead of humans. Users believe intelligent assistants provide personal privacy and justify that by considering intelligent assistants as confidants and non-judgmental. Users explain, in comparison, humans can talk about their secrets or personal matters with other humans while intelligent assistants are confidants. As a result, anthropomorphic features give superiority to intelligent assistants over humans and cause users to become committed.

In general, AI and anthropomorphic features foster human-intelligent machine relationships compared with human-nonintelligent machines by giving human-like features to intelligent machines. Also, using intelligent assistants to deliver a service could create a consistent interaction in service delivery which results in enhancing relational factors. Interacting with the same frontline employee every time (e.g., you always interact with Oscar) to receive a service could develop relational factors (e.g., trust (competent), rapport). This finding supports Andrews and Turner (2017) study that argued consistency and effective service delivery improves customer commitment and loyalty.

5.5 Conceptual Model of Customer Service Experience of AI-Based FLEs

Based on the discussed findings, this research proposes the following conceptual model (figure 5.1) for the customer service experience with AI-based organisational frontlines. The following sections will explain the model in depth.

5.5.1 First Engagement

The first time users engage with the intelligent assistants is either because of other people's recommendations (i.e., WOM and then previewing the intelligent assistant which causes users to engage with the intelligent assistant), or receiving the intelligent assistant as a gift, or additional item to their shopping basket (e.g., buy a TV and receive Alexa for free or half-price) (i.e., enablement). After the first engagement, they are gratified by the intelligent assistant's functionality which is mostly utilitarian and hedonic gratification (see arrow 1). Then the gratified person engages with the intelligent assistant again (see arrow 2).

5.5.2 Subsequent Engagements

A user's engagement with intelligent assistants is affected by different factors (motivation, reuse intention, technological sophistication, social presence, and privacy risk and uncertainty) at this stage. Motivation includes: the affordable cost, functionality, information quality, quick access, and skill and knowledge.

Users who engaged with other people's intelligent assistants the first time and were then gratified, become motivated to engage with intelligent assistant themselves due to the affordable cost. They justify this by explaining that the price is worth what it's going to do for them. The next motivation is functionality. Users engage with their intelligent assistants because intelligent assistants can provide a variety of services (e.g., from information seeking to operating smart home devices). They are also motivated to engage with the intelligent assistant because of the quality of the information they receive and/or having quick access to the service only using voice-based command. Finally, users are motivated to engage with the intelligent assistants due to their skill and knowledge (e.g., storytelling).

Obtained gratifications from a previous engagement creates intrinsic motivations that influence a user's intention to reuse the intelligent assistant. Moreover, users may engage with their intelligent assistants because of the empowerment they feel or ease of use (i.e., technological sophistication). Engaging with the intelligent assistants gives users the power to do things more conveniently and efficiently. Likewise, being voice activated increases an intelligent assistant's ease of use which affects a user's engagement. A sense of social presence perceived by users impacts users engagement through creating the illusion of interacting with another human. All of the factors mentioned above affect engagement positively. However, privacy risk and uncertainty negatively affect a user's engagement and cause diminishing use of or even termination of user engagement with the intelligent assistant.

Continuous engagement with the intelligent assistant fosters anthropomorphic features that result from AI through deep machine learning. For instance, engaging with intelligent assistants can teach it a person's daily routines and therefore can provide personalised services like turning off the light and playing sleep music when a user asks for the night routine (cognitive). Also due to continuous engagement, intelligent assistants can better learn behaviour and habits (mannerisms). Plus, constant engagement means that the intelligent assistant learns the user's accent and picks up words correctly which results in making interactions more enjoyable (auditory and cognitive) (see arrow 3).

Anthropomorphic features result in personalising the offered services by the intelligent assistant. Receiving personalised and advanced services create diverse gratifications for different users. For instance, cognitive aspects can build utilitarian gratification for users through creating convenience in receiving services (e.g., high quality information in real time). Cognitive anthropomorphic features can also create hedonic gratification by gaming. Users can play the 21 Question Game (i.e., the game when intelligent assistants choose a word and you must guess what it is after asking a maximum of 21 questions) with their intelligent assistant and obtain hedonic gratification.

Mannerism, on the one hand, gives the opportunity to users to ask a simple question which leads to obtaining utilitarian and hedonic gratifications. On the other hand, mannerism gives a sense of respect to users which results in social and hedonic gratification (e.g., enjoying the way an intelligent assistant interacts with a user).

Auditory anthropomorphic features, by creating convenient interactions through voice command, result in building utilitarian gratification for users. These anthropomorphic auditory features also build hedonic gratification for users through telling a joke or a story, and create social gratification through having bilateral interactions.

A sense of social presence and anthropomorphic features build social gratification for some users that triggers them to form an emotional affinity towards their intelligent assistants (see arrow 4).

Obtained gratifications by users may affect relational factors. Obtained utilitarian gratification builds trust and calculative commitment towards the intelligent assistant. Utilitarian gratification increases an intelligent assistant's competence and credibility to complete tasks properly. Moreover, hedonic gratification through, creating pleasant feelings, increase affective commitment in human-intelligent assistant relationships. Acquired social gratification and its resulting emotional affinity can form rapport with the intelligent assistant. Also social gratification by providing the sense of interacting with a human can enhance benevolence and even form affective commitment (see arrow 5).

Following on, formed relational factors by users towards the intelligent assistant influence a user's engagement especially from the emotional point of view. Additionally, relational factors can affect different engagement factors. For example, trust can decrease perceived privacy risk and uncertainty. In addition, rapport can enhance a sense of social presence. Moreover, commitment influences users to spread WOM (see arrow 6).

Anthropomorphic features can also affect trust directly. Cognitive intelligence by giving human capabilities to machines while diminishing human defects (e.g., human errors) increases an intelligent assistant’s competence. Cognitive intelligence is based on deep machine learning which enhances an intelligent assistant’s credibility. Auditory features also affect trust directly by making intelligent assistants more human-like. An intelligent assistant's humanised voice increases their competence and reliability (to some extent) compared with machine-like agents (see grey arrow).

In the proposed model, sequential procedures are identified by numbers, interactions follow the number sequence. But it should be considered that there is a possibility of withdrawal from applying the intelligent assistant either permanently or temporarily in each stage for reasons this research has not been able to identify in the empirical data, apart from the only comment regarding privacy risk and uncertainty.

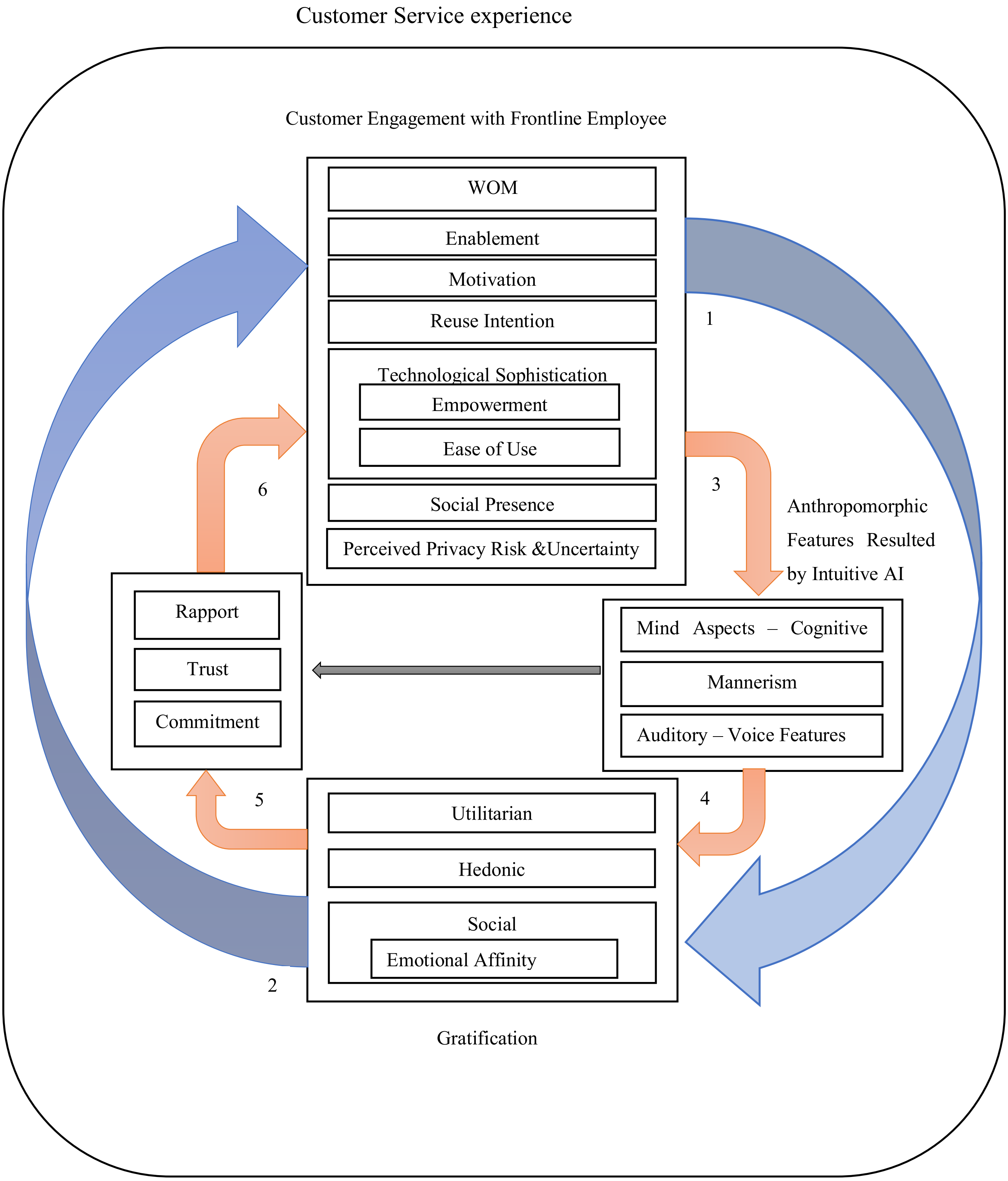

Figure 5-1: The Concluded Model of the Customer Experience of Virtual Intelligent Frontline Employees

5.6 Conclusion

This research identifies gratification as a significant factor that influences the customer service experience when intelligent assistants fulfil the role of frontline employees. Also, research data shows gratifications are key drivers of relational behaviour despite of the presence of privacy risk and uncertainty. Intuitive AI and its resulting anthropomorphic features are the main sources of building stability in human-intelligent machine relationships providing advantages to virtual frontline employees over humans.

In human-human service encounters (face-to-face, phone, email, etc.) customers may engage with different frontline employees in different interactions while in human-intelligent machine service encounters customers engage with a frontline employee who is always the same (e.g., Alexa or Oscar Air New Zealand chatbot). For instance, imagine you have a problem with your insurance. You call to complain, and John answers the phone, but he cannot solve your problem and so passes the phone onto Sara. You now have to explain everything again. Sara is not sure about the answer and needs to ask her supervisor. She asks you to call later. You call again and this time Tom answers the phone. You have to explain everything for a third time. If it were an intelligent assistant the whole problem would be dealt with, by an intelligent assistant, even if you call later to follow up. These differences cause customers in human-human service encounters to build a relationship with the organisation, though in human-intelligent machine service encounters customers develop a relationship with a machine affecting customer future engagement and intention to use.

In human-intelligent machine service encounters, intuitive AI exacerbates privacy risk and uncertainty with interactions. Privacy risk and uncertainty and lack of information regarding AI affect the formation of a relationship between humans and intelligent machines. Research findings suggest that experienced gratification moderates the effect of privacy risk and uncertainty.

Moreover, in human-intelligent machine communications due to the superiority of machines in removing human barriers (e.g., getting into a temper) and being a personalised frontline employee (e.g., interacting with an employee that can learn your preferences from your previous behaviours) relative to humans, means intelligent machines are more capable of creating stable gratifications.

Chapter 6 Conclusion

6.1 Introduction

This chapter presents a summary of the key findings and the contributions of the study that adds to existing knowledge regarding how the customer service experience is changing at the organisational frontline as a result of AI-based frontline employees (i.e., intelligent assistant). The research limitations and how they could have affected research findings will also be explained. This research also proposes a future research agenda.

6.2 Summary of Key Findings

This study provides insights into how AI-based frontline employees can enhance the customer service experience in service encounters by addressing the research questions: (RQ1) How do intuitive AI-based organisational frontlines affect customer engagement in service encounters? (RQ2) How do intuitive AI-based organisational frontlines affect perceived gratification by customers in service encounters? (RQ3) How do intuitive AI-based organisational frontlines affect human-machine relationships in service encounters? And main research question; (RQ) How do intuitive AI-based organisational frontlines affect the customer service experience? The findings illustrate that the first time most users engage with intelligent assistants is because of enablement or WOM and subsequently, because of the AI-evoked gratifications they experience, reengage with intelligent assistants to address their needs. Users, because of the benefits of anthropomorphic features (e.g., ease of use, voice-based interfaces, functionality, etc.) become motivated to reengage with AI-based frontline employees. Anthropomorphic features, by creating a sense of social presence influence users to form emotional attachments, and enhance engagement. Moreover, voice-based attributes of intelligent assistants facilitate human-to-machine interactions and increase ease of use that leads to obtaining gratifications. Experienced gratifications (utilitarian, hedonic, and social) positively influence users to reengage with the intelligent assistant.

Individuals gain gratifications from using intelligent assistants so they request and receive services, and in turn, obtained gratifications make their service experience more pleasant and increases their intention to use the intelligent assistants again. The majority of acquired gratifications are the result of applying intuitive AI. Anthropomorphic features enabled by intuitive AI give human characteristics to the intelligent machine, and this creates a sense of interacting with a human. A sense of social presence contributes to developing different utilitarian, hedonic and social gratifications for users.

Having a different type of human-to-machine interaction compared to the past (e.g., bilateral interactions) makes it possible for customers to have social interactions with intelligent assistants and gain social and hedonic gratification directly from interacting with the AI-based frontline employees. This contrasts with previous experiences where machines were merely a medium for human-to-human interactions. Social interaction with intelligent assistants, and the resulting sense of a social presence through anthropomorphic features, trigger customers to develop an emotional affinity towards intelligent assistants and to become emotionally involved with them. Accordingly, perceived emotional affinity causes customers to form a rapport and increases their intention to use AI-based frontline employees.

Anthropomorphic features affect trust positively by enhancing perceived levels of competence, credibility, reliability, and benevolence in AI-based frontline employees. In contrast, anthropomorphic features also affect trust negatively by creating privacy risk and uncertainty. Consequently, users form different levels of trust based on the perceived benefits of the costs of engagement with AI-based frontline employees. These results identified that user difficulties in assessing risk because of imperfect information resulted in the formation of trust based on obtained gratifications. Moreover, due to acquiring social and hedonic gratifications, users developed affective commitment towards AI-based frontline employees. Relational factors also are influenced by mannerisms. Mannerism affects perceived gratifications and as a result, relational factors.

6.3 Theoretical Contributions

This research aimed to investigate the effects of intuitive intelligent assistants on the customer service experience. For this purpose, it draws on use and gratification theory, social exchange theory, and anthropomorphism theory to examine the role of intelligent assistants displaying anthropomorphic features within the customer service experience. Relevant to this, three contributions have been identified in this research.

One of the primary theoretical contributions of this research is within the use and gratification theory. Historically, gratification was studied as an outcome of engagement since users engage with media and content to address their psychological and social needs. However, these research results illustrate that engagement can be the outcome of gratification (e.g., being gratified for the first time (e.g., when another person engages with the intelligent assistant and asks it to tell a joke then a second person in the same environment obtains hedonic gratification) and decide to engage (e.g., buy)). Moreover, it contributes to expanding use and gratification theory by identifying how users obtain social and hedonic gratification through communicating directly with the media itself, and not with media merely as a medium of human-human communication.

Another contribution of this research is related to affective commitment and social exchange theory. Anthropomorphic features (e.g., humanised voice, cognitive intelligence, mannerisms) give a sense of social presence to intelligent assistants, and interacting with them can develop emotional affinity and rapport for users. Hedonic and social gratification (e.g., emotional affinity, enjoyment) and rapport could lead to forming affective commitment. This research contributes to the developing human-machine relationship literature by recognising how affective commitment may contribute to human-to-intelligent assistant relationships.

Lastly, this research contributes towards the concept of mannerism within the literature in two aspects. First, it contributes to expanding anthropomorphism theory by demonstrating how anthropomorphic features may cause users to attribute human mannerisms to intelligent assistants (previous literature mentioned attributing behavioural aspects, emotional states, and mental states (Awad et al., 2018; Malle et al., 2019)). Second, it contributes to the human-machine relationship literature by illustrating how intuitive AI and its anthropomorphic features create anxiety-free interactions (e.g., removing human-human relationship defects: being judged, humiliated, or disclosing an individual's information that may lead to uncomfortable questions), facilitate the building of trust through verbal acknowledgment (i.e., the way intelligent assistants behave) and rapport. Attributing a human's manner to intelligent assistants makes them more credible as humans compared to former technologies, which increases trust.

6.4 Methodological Contribution

Due to the novelty of merging two qualitative methods which are in essence different data sets (i.e., interview and social data) with different analytical strategies (i.e., computer-assisted (Nvivo)) and text mining and computer-based coding (Leximancer), this research contributes towards acquiring the same knowledge about the unit of analysis (i.e., a human's perception of interacting with intelligent assistants) through two different data sets which result in building more consistent results.

6.5 Managerial Implications

Having intelligent assistants as frontline employees can bring some advantages and disadvantages for organisations. Hence, this research highlights the following implications for managers:

- By using intelligent assistants, organisations can remove queue lines while offering personalised services. They can handle thousands of interactions simultaneously without affecting response speed and accuracy. Intelligent assistants can identify customers quickly and answer a variety of questions. When customers contact the organisation, they always interact with their personalised intelligent assistant (e.g., Sam (a customer) calls a service centre and speaks with Sara (a human agent). He introduces himself and explains his problem to her. Sara then asks him to talk with her supervisor, so Sam is passed to Sara's supervisor, and he must explain the problem from the beginning. The supervisor then asks Sam to talk with an IT support person. Sam talks to IT support and needs to explain again for the third time. If the organisation were to use intelligent assistants, Sam would only have to talk with one intelligent assistant).

- Intelligent assistants, over time, become more mature as they process and develop algorithms (i.e., deep learning). As they learn, they can personalise and customise the service they offer based on the frequency of interactions with users (e.g., learning user's accent, preferences, habits).

- Intelligent assistants can help managers to develop their organisational frontline when there are crises (e.g., COVID-19), or in times where face-to-face interactions are limited (e.g., outside of business hours 24/7), so that they are able to offer services with superior or similar quality to human frontline employees.

- By recognising different accents intelligent assistants can improve customer-employee interactions and increase customer perceived gratifications and satisfaction.

- Applying intelligent assistants as organisational frontlines helps organisations to record customer-to-employee interactions automatically. Whereas in the case of human employee-to-customer interactions only phone calls in call service centres are recorded, and in face-to-face interactions human frontline employees need to record them after finishing the interaction and may face some problems (e.g., recall).

- Intelligent assistants can bring personal privacy to the customer-organisation relationship. Since human employees can disclose customer's information to third parties outside of the organisation, using intelligent assistants would mean that customer's information would remain inside of the organisation.

- The intangible and interactive nature of services often causes customers to rely on the behaviour of frontline service employees when judging the quality of a service (Hennig-Thurau, 2004). So, managers can benefit from the consistency of machine behaviour to enhance perceived service quality. Intelligent assistants can behave in a positive manner even when a customer behaves impolitely. They are not affected by environmental conditions and work crises (e.g., fatigue and stress).

- When discussing technology-based service offerings, the focus is usually on functional and technical benefits (e.g., utilitarian gratifications), however it should also concentrate on social benefits derived by customers through their face-to-face interactions with frontline employees. Since customers in this research clearly do not rely only on the technological aspects and form emotional and social dimensions as part of the relationship, service managers need to use the advantage of the social benefits that customers derive through interacting with AI-based frontline employees. Organisations can use the social advantages of AI-based organisational frontlines to optimise their relationship with customers.

- Previous machines lacked the social benefits of face-to-face interactions in service encounters. However, intelligent assistants can optimise the organisation-customer relationship by encompassing the social benefits of face-to-face interactions. Customers can have bilateral interactions with intelligent assistants which may lead to forming emotional and social dimensions within the relationship.

- Having intelligent assistants as frontline employees can help organisations keep their knowledge within the organisation and prevent losing their resources in the case of an employee moving to another organisation (e.g., after relocating a human employee to another company their customers may prefer to buy from that company).

- Organisation that incorporate intelligent assistants have two options 1) custom-built intelligent assistants, 2) pre-built intelligent assistants. If they use custom-built intelligent assistants, they are not developed and need big databases to feed them and time to learn from customers behaviour. This can result in dissatisfaction from users in the beginning. If they use the second option (e.g., they rent an interface from other companies like Microsoft or Amazon), there is a risk of a third party using their information. It also increases the privacy risk and uncertainty for customers (e.g., being heard and recorded by another company). However, organisations can mitigate these risks by clarifying their privacy policy for customers regarding why and where they record and save customer's information and who the third party is.

6.6 Limitations

AI is developing rapidly which leads to constant evolution and development of intelligent assistants. Consequently, the customer experience of the offered service by intelligent assistants will improve over time, and this can affect research findings in two aspects. First, the user's perception of the received service by intelligent assistants could be different depending on the time they apply it. Second, if a researcher repeats the research the results would be different due to AI changes (e.g., the programmer could add an empathy or ethical features to intelligent assistants in the future).

Another limitation relates to the nature of the qualitative interpretive research. The outcomes of the research are limited to the researcher's interpretation, since the research data was coded and interpreted based on the researcher's background and observations during each interview. To diminish the effects of this limitation some actions were taken. Having constant meetings with supervisors to discuss the coding process and emerging themes as well as using a second dataset for triangulating the results.

The next limitation relates to the generalisability of the findings. Although the findings of qualitative research cannot be used for statistical inference towards a population, they aim for methodological generalisability. Results display the different views, experiences, consequences or other circumstances under study and the factors that form and influence them. This kind of generalisation can be tackled by the principles of validity and reliability that let the reader know to what extent identified patterns and derived conclusions reflect reality and can be trusted.

6.7 Directions for Future Research

Although this research concluded with a set of findings in the service context, further research gaps were also identified which need further research to be answered.

Whilst this research identifies that customers form social and emotional relationships with AI-based organisational frontlines, this requires further investigation. Additional research could investigate the logic behind building three different kinds of relationships (i.e., as a friend, acquaintance, and employee) with AI-based organisational frontlines. It is also important to study social and emotional interactions more, the types between different individuals, and explore the role of these in maintaining the relationship.

There is also a need to study the reasons for forming different levels of trust, from blanket trust to distrust. This research only identifies a different level of trust in human-intelligent machine relationships. It will be interesting to explore which trust dimensions lead to building each level of trust in the human-intelligent machine relationship.

This research applied intelligent assistants (Siri, Alexa, Google Assistant) for research, because they are currently the most advanced globally. While AI is constantly developing, it will be rewarding to study the more advanced or mature intuitive level of AI and/or a new level of AI (e.g., empathetic AI) and the effects on the customer service experience.

AI will become a part of every organisation's strategy to attain competitive advantage. Different organisations apply AI to improve their service delivery systems or employee's productivity. While this research was done in a business-to-customer context, future research could explore the human-intelligent assistant relationship, or even the intelligent assistant-intelligent assistant relationship (i.e., when both companies use intelligent assistants as a frontline employee) and the role of humans in situations where intelligent assistants are frontline employees in a business-to-business context.

Privacy risk and uncertainty emerged in this research as the only factor that could affect customer disengagement. Different research approach can investigate other reasons of customer disengagement from AI-based organisational frontlines which lead to relationship termination and service failure.

Finally, this research explores the effect of applying AI-based organisational frontlines on customer service experiences. Future research can use a confirmatory technique (e.g., Structural Equation Modelling, etc.,) to test the validity of this research's model and the relationship between variables.

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Appendix

Appendix 1. Interview protocol

Purpose of protocol: To make explicit the procedures of data collection.

Research questions: How is the customer service experience of AI-based FLEs?

Goal: Identify and understand the factors which affect customer experience of intuitive AI-based service encounters that can be used by organisations to improve their organisational frontline.

Data collection procedures for semi-structured in-depth interviews:

Site: Across the world by the Zoom application interface

Period: April to May 2020.

Respondents are recruited through posting announcements on the Siri, Alexa, and Google Assistant user's Facebook group pages and the snowball method.

Questions:

1. Could you tell me about your intelligent assistant?
2. How is your experience of your intelligent assistant?
3. How was life before using your intelligent assistant?
4. How it affects you?
5. What do you enjoy about it?
6. Is there any subject about your intelligent assistant that makes you more cautious about using it? Could you explain this more?
7. If instead of your intelligent assistant someone can offer these services to you which one do you prefer? Why?
8. Is there anything special about your intelligent assistant that you would like to share with me? (If yes, please let me know)

Appendix 2. Interview information sheet and consent form

[Reference Number: *D20/080*]
[*26.03.2020*]

Studying the relationship between customer service experience and customer engagement resulted in the intelligent organisational frontline

INFORMATION SHEET FOR PARTICIPANTS

Thank you for showing an interest in this project. Please read this information sheet carefully before deciding whether or not to participate. If you decide to participate we thank you. If you decide not to take part there will be no disadvantage to you and we thank you for considering our request.

What is the Aim of the Project?

This project aims to explore the factors that evoke user trust in intelligent machines. It investigates about the relationship between user's calculative commitment and user experiences of human-machine relational exchange in artificial intuitive intelligence-based organisational frontlines and the relationship between artificial intuitive intelligence-based organisational frontline and user experiences. This project is being undertaken as part of the requirements for PhD in Marketing.

What Types of Participants are being sought?

The researcher is looking for participants who use the virtual assistant or chatbots in the role of frontline employees. Participants aged 18 years and over. Recruitment of participate will be done online through social media such as Facebook and LinkedIn as well as snowball sampling where participants may refer other qualified participants to the researcher. At the end of the interviews, a lottery of $50x6 vouchers will be drawn within the participants.

What will Participants be asked to do?

The participants will be asked regarding their perceptions, attitudes and behavioural intentions related to their interactions with virtual assistants.
The interview will explore the participant's experience of using supersmart virtual assistants and the factors that affect their interactions.

What Data or Information will be collected and what use will be made of it?

Should you agree to take part in this project, you will be asked to:
Attend an online zoom interview that will take approximately 40 to 60 minutes. With your permission, The interview will be video recorded and the recording will be subsequently transcribed by zoom. During the interview you will be asked about your experience of using the virtual assistant and interacting with it. All interviews will be confidential and no data will be attributable to individuals in a way that enables those individuals to be identified. We assign pseudonyms to all participants and identifying data will be destroyed once the recordings have been transcribed. The results of the project may be published and will be available in the University of Otago Library (Dunedin, New Zealand).

Only members of the research team (Arezoo Fakhimi, Dr Tony Garry, Dr Sergio Biggemann) will have access to the data which will be stored under password protection. Data obtained as a result of this research will be retained for at least five years in secure storage. Any personal information held on participants may be destroyed at the completion of the research even though the data derived from the research will, in most cases, be kept longer.

This project involves an open-questioning technique. The general line of questioning focuses on participants experiences of interacting with the virtual assistant. However, the precise nature of the questions which will be asked have not been determined in advance, and will depend on the way in which the interview develops. Consequently, although the University of Otago Human Ethics Committee is aware of the general areas to be explored in the interview, the Committee has not been able to review the precise questions to be used. In the event that the line of questioning does develop in such a way that you feel hesitant or uncomfortable, you are reminded of your right to decline to answer any particular question(s) and also that you may withdraw from the project at any stage without any disadvantage to yourself of any kind.

Can Participants change their mind and withdraw from the project?

You may withdraw from participation in the project at any time and without any disadvantage to yourself of any kind.

What if Participants have any Questions?

If you have any questions about our project, either now or in the future, please feel free to contact either:-

Arezoo Fakhimi	and	Dr. Tony Garry
Department of Marketing		Department of Executive Programmes
University Telephone Number: +643479847695		University Telephone Number:
Email Address: arezoo.fakhimi@postgrad.otago.ac.nz		Email Address: tony.garry@otago.ac.nz

This study has been approved by the Department stated above. However, if you have any concerns about the ethical conduct of the research you may contact the University of Otago Human Ethics Committee through the Human Ethics Committee Administrator (ph +643 479 8256 or email gary.witte@otago.ac.nz). Any issues you raise will be treated in confidence and investigated and you will be informed of the outcome.

Studying the Relationship between Customer Service Experience and Customer Engagement at the Intelligent Organisational Frontline

CONSENT FORM FOR
PARTICIPANTS

I have read the Information Sheet concerning this project and understand what it is about. All my questions have been answered to my satisfaction. I understand that I am free to request further information at any stage.

I know that:-

My participation in the project is entirely voluntary;

I am free to withdraw from the project at any time

Personal identifying information gathered through video recording will be destroyed at the conclusion of the project but any raw data on which the results of the project depend will be retained in secure storage for at least five years;

This project involves an open-questioning technique. The general line of questioning includes user's experiences of interacting with the intelligent organisational frontlines. However, the precise nature of the questions which will be asked have not been determined in advance but will depend on the way in which the interview develops and that in the event.

If the line of questioning develops in such a way that I feel hesitant or uncomfortable I may decline to answer any particular question(s) and/or may withdraw from the project without any disadvantage of any kind.

I understand I am eligible to 50$ voucher award as it will be drawn by lottery at the end.

The results of the project may be published and will be available in the University of Otago Library (Dunedin, New Zealand) but every attempt will be made to preserve my anonymity, should I choose to remain anonymous.

I agree to take part in this project.

....

(Signature of participant) (Date)

....

(Printed Name)

[*Options for Anonymity: in the case where your participants are public figures, artists, musicians, politicians or government officials, and it is anticipated that they will be identified/identifiable, you can offer the following options, which should match the paragraph in the Information Sheet which states "On the Consent Form you will be given options regarding your anonymity. Please be aware that should you wish we will make every attempt to preserve your anonymity. However, with your consent, there are some cases where it would be preferable to attribute contributions made to individual participants. It is absolutely up to you which of these options you prefer."]*

[8. I, as the participant: a) agree to being named in the research, ☐ OR;

b) would rather remain anonymous.] ☐

Appendix 3. Ethics Approval

D20/080

UNIVERSITY of OTAGO
Te Whare Wānanga o Otāgo
NEW ZEALAND

Academic Services
Manager, Academic Committees, Mr Gary Witte

30 March 2020

Assoc. Prof. T Garry
Department of Marketing
Division of Commerce
School of Business

Dear Assoc. Prof. Garry,

I am writing to confirm for you the status of your proposal entitled "**Studying the relationship between customer service experience and customer engagement resulted in the intelligent organizational frontline**", which was originally received on March 26, 2020. The Human Ethics Committee's reference number for this proposal is **D20/080**.

The above application was Category B and had therefore been considered within the Department or School. The outcome was subsequently reviewed by the University of Otago Human Ethics Committee. The outcome of that consideration was that the proposal was approved, especially in light of the interviews being conducted by zoom.

Approval is for up to three years from the date of HOD approval. If this project has not been completed within three years of this date, re-approval must be requested. If the nature, consent, location, procedures or personnel of your approved application change, please advise me in writing.

Yours sincerely,

Gary Witte

Mr Gary Witte
Manager, Academic Committees
Tel: 479 8256
Email: gary.witte@otago.ac.nz